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A Survey of Machine Learning Algorithms Based Forest Fires Prediction and Detection Systems

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Abstract. Forest fires are one of the major environmental concerns, each year millions of hectares are destroyed over the world, causing economic and ecological damage as well as human lives. Thus, predicting such an environmental issue becomes a critical concern to mitigate this threat. Several technologies and new methods have been proposed to predict and detect forest fires. The trend is toward the integration of artificial intelligence to automate the prediction and detection of fire occurrence. This paper presents a comprehensive survey of the machine learning algorithms based forest fires prediction and detection systems. First, a brief introduction to the forest fire concern is given. Then, various methods and systems in forest fires prediction and detection systems are reviewed. Besides works that reported fire prediction and detection systems, studies that assessed the factors influencing the fire occurrence and risk are discussed. The main issues and outcomes within each study are presented and discussed.

Keywords: Forest fires, Fire detection system, Fire prediction system, Logistic regression, Machine learning, Neural network

1. Introduction

Forests [1] play a crucial role in the earth's ecological balance. However, these natural resources are threatened by fires, which are related to natural and human factors. Forest fire [2, 3] is a disaster that entails considerable negative effects on natural environment, economic and human resources. The global warming and the threat of flora and fauna species lives are the forest fires consequences. Considering the threat caused by forest fires, early fire prediction and detection are important measures that significantly reduce damages caused by this disaster and reduce firefighting efforts. The first measure of the fire management is the forest fires prediction that concerns basically, the forest fire occurrence prediction, i.e., forecasting the forest fire outbreak probability before its initial ignition; by modeling the relationship between the fire risk and the influential factors such as weather conditions or fuel content. The main objective is to predict when and

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where the fire can occur to ovoid its ignition and spread. The prediction can also be considered after the initial-fire ignition; in this case the issue is about predicting the behavior of the forest fire, i.e., forecasting the fire spread evolution. The forest fire behavior prediction concerns the level of variability according to the fire environment (weather conditions, moisture content, fuel content and even human presences). For example the forest fires time-resolved spatial evolution prediction and the fire spread rate prediction with respect to the wind speed. In others hand, the forest fires prediction after the initial-ignition can be performed to predict the amount of land burnt during forest fire, in order to classify the fire into small or big fire. The prediction in this case is useful in preparing firefighting strategies, for example deciding which actions to undertake to manage the emergency; such as the proper firefighting resources allocation.

The second measure is the forest fires detection that concerns the identification and location of fires that are already active. The main objective is to provide the exact localization and the fire alarm at early stage before fire spread over a large area, making its beyond control. Forest fires detection is performed by several monitoring techniques/methods to put the fire out before its spread and shorten the reaction time to reduce the damaging effects and casualties of the forest fires. In fact, we can categorize the forest fires detection and monitoring systems into two main groups, namely the traditional forest fires detection systems (direct monitoring based on human observation) and the automatic detection systems (distance monitoring). Traditional forest fires detection and monitoring systems include mainly watchtowers or aerial patrols. However, these traditional methods are tedious and mainly based on operators that manage the alarms. The exploration of new methods for forest fires prediction, detection and monitoring as alternatives to the old ones becomes an emergency. In this context; several technologies and systems have been proposed to early detect fires, e.g., systems employing charge-coupled device cameras and infrared detectors, satellite systems, Wireless Sensor Networks (WSNs) [4, 5] and the Unmanned Aerial Vehicles (UAVs). Besides the conventional methods and techniques that have been proposed for automatic detection of forest fires [6]; additional studies have been conducted to combine fire detection system with data mining techniques, i.e. machine learning algorithms for intelligent systems that can analyze the data with accurate and rapid results.

Data mining [7] refers to a set of computer-based tools, which permit exploratory data analysis; to reveal patterns and relationships in databases using machine learning (ML) algorithms. Substantial studies have investigated the application of the machine learning algorithms for forest fires prediction and detection purposes. In this paper, we review methods based on ML algorithms for forest fires prediction and detection systems reported in the current literature and we discuss their strengths and weaknesses by analyzing the reported results.

This paper is organized as follows: Section 2 presents an overview of the machine learning based forest fires prediction and detection systems. In this section, we focus on the mostly employed machine learning algorithms for forest fires prediction and detection systems, namely works discussing systems based on neural networks, logistic regression and decision tree and its ensembles. Section 3 undertakes a review of the forest fires prediction and detection systems based on additional ML algorithms, besides the mostly used ML algorithms in fire modeling. A discussion regarding the important issues within the methods exposed in Sects. 2 and 3 is given in Sect. 4. Finally, Sect. 5 concludes this paper.

2. Machine Learning-based Forest Fires Prediction and Detection Systems

The machine learning is a subset of the artificial intelligence (AI), allowing machines to make decisions by learning from data. Substantial studies have investigated the application of the artificial intelligence in numerous applications, among them the forest fires prediction and detection. The introduction of AI in the forest fires prediction and detection systems is a very promising direction. In this context, a lot of researches have been carried out for fire occurrence modeling to take advantages of the AI. Almost all types of machine learning methods are exploited for this issue. These machine learning based models are also employed as units in other forest fires prediction and detection systems based on new technologies. In fact the trend is toward the integration of artificial intelligence to the WSN and UAV based systems to automate the prediction and detection of fire occurrence. In this section, we start by reviewing the mostly applied ML algorithms for forest fires modeling, namely the Artificial Neural Network (ANN), the logistic regression and the decision tree and its ensembles. We also introduce examples of works that have combined the machine learning algorithms (mainly the ANN, DT, Bayesian and fuzzy logic) with the WSN technology.

2.1. Neural Networks Based Forest Fires Prediction and Detection Systems

Artificial Neural Networks [8] are computational models that are inspired by the biological neural networks of the brain. The basic processing units in the ANNs are the artificial neurons, which are arranged in layers interconnected by weighted connections. The main computational characteristics associated with ANNs are parallelism, modularity, high tolerance of noisy data and their ability to learn by examples and classify novel data patterns on which they have not been trained. These characteristics made the ANN models applicable in several fields such as medical diagnosis, image and signal processing, financial forecasting, and pattern recognition. There are different types of neural network models, which are categorized according to their learning mode, namely the supervised ANNs (e.g., the Multi-Layer Perceptron (MLP) trained using the back-propagation algorithm (BPN)) and the unsupervised ANNs (e.g., the Kohonen's self-organizing feature map, which is a two layers self-organizing network with a competitive learning model). The neural networks are powerful techniques for classification problems; they have been applied in a variety of applications; due to their robustness and good accuracy. In the case of forest fires prediction and detection, this type of machine learning is widely employed as a single system or integrated in the WSN or UAV based fire detection systems. The introduction of new communication technologies such as WSN and UAV combined with the artificial intelligence is a

Table 1
Summary of Some Studies Regarding ANNs Based Forest Fires Prediction and Detection Systems

References	Methods	Type of dataset	The main reported results	Tasks
Arrue et al. [16]	The Back Propagation Network (BPN) The Radial Base Function Network (RBFN) Dynamic Learning Vector Quantization (DLVQ)	Multi-source data: Meteorological Geographical information data The visual camera and the infrared camera data	False alarm rate is 1.93% Detection rate over 98%	False alarm reduction system development
Yu et al. [25]	MLP with WSN	Temperature Relative humidity, Smoke Wind speed	Average communication load ratio (with NN method and the one without NN method) in range of: 2.5% (100 sensor nodes) to 8% (50 sensor nodes)	Real time forest fire detection using WSN
Vasilakos et al. [14]	MLP BPN	Meteorological data Vegetation and topological data Human presence	Percentage of the most influencing variables (PI): Occurrence of rainfall in the last 24 h: 35.9% Temperature: 28.7% 10-h Fuel moisture 60.3% Aspect: 16.9% Primary road network: 17.3% Month of the year: 14.3%	Estimation of variables' importance on a fire ignition danger scheme
Maeda et al. [20]	Multilayer feedforward networks (MLFN)	The NDVI composite MODIS data	Accuracy: 90% A MSE value: 0.07	High risk FFD based on information in pixels of multi-temporal satellite images
Dimuccio et al. [9]	Back-propagation neural network (BPN)	GIS based data	An agreement of 78%	Forest fire susceptibility map construction

Table 1 continued

References	Methods	Type of dataset	The main reported results	Tasks
Liu et al. [18]	Multiple layer back propagation artificial neural network	Temperature Relative humidity Infrared light Visible light	Detection Accuracy: ≈90% for the distance between the sensor node and a fire of 10 cm ≈40% for the distance between the sensor node and a fire of 20 cm	Forest fire multi-criteria detection system using WSN
Özbayoğlu and Bozer [13]	MLP RBFN SVM Fuzzy logic	Meteorological data: Temperature Relative humidity Wind speed Climate and topography data	1. MLP model: Accuracy: 65% RMSE: 15.85 MAE: 4.11 MAPE: 51 2. RBFN model: RMSE: 18.35 MAE: 4.05 MAPE: 54 3. SVM model RMSE: 7.33 MAE: 3.36 MAPE: 69	Burned forest area identification
Kalabokidis et al. [17]	BPN (Vasilakos as a danger module)	Satellite data (images) and natural data	Deliverable: AHP DSS modular system	Development of Auto Hazard Pro-Decision Support Fire detection System (AHP DSS)
Karouni et al. [11]	BPN DT	Meteorological data	Results for a 4-inputs feed forward NN: Precision: 98.9%, Specificity: 76.9%, Sensitivity: 94.2%, Accuracy: 93.5%	Forest fires prediction

Table 1
continued

References	Methods	Type of dataset	The main reported results	Tasks
Zhang et al. [22]	Deep CNN SVM	237 fire images	Accuracies 1. A global image-level testing Deep CNN: 90% 2. Patches location SVM: 92.2% CNN: 93.1%	Fire occurrence detection in images
Yan et al. [26]	MLP	Smoke CO_2 Temperature (1160 data samples)	Accuracy: 82.5%	Real time identification of a dominant combustion phases
Muhammad et al. [19]	CNN	68,457 images CCTV surveillance cameras	Accuracy: 94.39% Precision: 0.82 Recall: 0.98 F-Measure: 0.89	A fine-tuned CCN surveillance camera based fire detection model (FFD in images)
Kinaneva et al. [32]	Multilayer NN	Thermal camera data (smoke in the forest images)	NA (Not Available)	Forest fires detection system based UAV
Hodges et al. [10]	CNN (DCIGN)	Landscapes Fuel type Weather conditions (mainly wind)	Mean precision: 97% Sensitivity: 92% F-measure: 93%	Time-resolved spatial evolution prediction of the wildland fire

promising direction, which is exploited for automatic forest fires detection systems. In the next paragraphs, we give an overview of existing studies related to the ANNs based forest fires prediction systems followed by the studies concerning the forest fires detection systems.

2.1.1. Forest Fires Prediction A multiplicity of ANNs [9–14] has been included in the forest fires prediction systems. For example the work exposed in Vasilakos et al. [14] dealt with a back-propagation neural network based sensitivity analysis system. Vasilakos et al. developed a fire ignition scheme for the Lesvos Island in Greece. They proposed an approach to distinguish the influence of several variables in a fire ignition risk scheme. According to this study, the most influencing weather variable is the rainfall in the last 24 h followed by temperature, wind speed, and relative humidity. This study also revealed that the most influencing variable with respect to the vegetation and topographical data is the 10-h fuel moisture content followed by fuel models, aspect, and elevation. Regarding the human presence and socioeconomic impacts, the fire risk index is mostly influenced by the month of the year followed by proximities to urban areas, landfills and main roads. In Dimuccio et al. [9], the authors combined the Global Information System (GIS) analysis and the ANN modeling to construct the Forest-Fire Susceptibility (FFS) map of the Central Portugal. They first determined the rating for categories of eight fire-related factors (topographic slope and aspect, road density, viewsheds, land cover, landsat Normalized Difference Vegetation Index (NDVI), precipitation and population density) using a frequency-probabilistic procedure. The back-propagation artificial neural network was then employed for the fire-related factors weights assignment. The obtained ratings and weights were then integrated using the GIS to develop the FFS index map. The FFS index map was evaluated using data of areas that were burnt from 1990 to 2007; the reported results indicated an agreement of 78%. The back propagation forward artificial neural network was also studied in Karouni et al. [11] for fire occurrence prediction. The reported maximum values for the 4-inputs feed forward network were about 98.9%, 76.9%, 94.2% and 93.5% for the precision, specificity, sensitivity and accuracy, respectively. The decision tree has been also investigated in this work.

In another work [13] different machine learning models were investigated for the burned forest area identification. The models used in this study were the MLP, Radial Basis Function Networks (RBFN), the Support Vector Machine (SVM) and the fuzzy logic. The data employed was collected from 7920 forest fires between 2000 and 2009 including meteorological (relative humidity, wind speed and temperature), climate and topography data. The authors approach is based on identifying the burned area clusters considering five forest fires sizes (very small fire, small fire, medium fire, big fire and very big fire). The reported results in terms of success rate with the MLP model were 53.02% and 62.89% for 5 clusters and 3 output clusters, respectively. The reported comparison results showed that the best model was the MLP with a global accuracy about 65% (using humidity and wind speed) and that the RBFN presented poor performances. Additional metrics were used in this study for the models evaluation, namely the

Table 2
Summary of Some Studies Regarding the Forest Fires Prediction and Detection Systems Based on the Logistic Regression and DT and its Ensembles Algorithms

References	Methods	Type of dataset	The main reported results	Tasks
Vega-Garcia et al. [42]	Logistic regression RBFN	GIS based data	ANN accuracies: Correctly predicted no-fire: 85% Correctly predicted fire: 78%	Comparative study of ANN and logistic regression models in the context of human-caused fire prediction system
De Vasconcelos et al. [40]	Logistic regression MLP (with genetic algorithm)	Information in a raster GIS Date of occurrence Place and county Geographic coordinates Cause of ignition Land use and burned area	1. Logistic regression accuracies: 78.8% (ignition), 74% (no ignition) 2. ANN accuracies: 75.7% (ignition), 87.8% (no ignition)	Development of a model for the wildfire ignition probability prediction
Chang et al. (2004)	Logistic regression	Topography Vegetation types Meteorological and climate conditions Human activity	Accuracy: 85.7%	Fire ignition prediction
Stojanova et al. [48]	Logistic regression DT and its ensembles	GIS data Multi-temporal MODIS data Meteorological ALADIN data	Accuracies: DT: 81.2% Bagging DT: 84.9% Boosting DT: 84.4%	Forest fire prediction system
Lozano et al. [52]	CART	Environmental factors: the vegetation status and type, accessibility, fire history and topography	Accuracy: 88.39%	Special models for fire occurrence probability at different special observations
Catry et al. [38]	Logistic regression	GIS based data	Global accuracy: 79.8% correctly predicted ignitions: 78.2% Correctly predicted no-ignitions: 82.7%	Fire ignition risk map model based on the human activities and presence factors

Table 2 continued

References	Methods	Type of dataset	The main reported results	Tasks
Stojanova et al. [49]	BT RF Logistic regression Naïve Bayesian (NB) SVM	GIS data (geographical) Remote Sensing imagery Weather condition (ALADIN model)	For continental Slovenia region 1. BT: Accuracy: 84.9% Recall: 84.7% 2. RF: Accuracy: 82.5% Recall: 86.8% 3. Logistic regression: Accuracy: 83% Recall: 84.2% 4. NB: Accuracy: 81% Recall: 81% 5. SVM: Accuracy: 83% Recall: 84.2%	Forest fire outbreaks risk estimation
Padilla and Vega-Garcıa [43]	Logistic regression	Weather data Geographic characteristics Historical records of daily fire	Total percentage of correctly predicted fire in range of 47.4% to 82.6% – AUC value in range of 0.52 to 0.86	Human-caused fire occurrence modeling

Table 2 continued

References	Methods	Type of dataset	The main reported results	Tasks
Oliveira et al. [51]	Random Forest (RF) Multiple Linear Regression (MLR)	37 variables extracted from several databases covering physical, socio-economic and demographic aspects	1. RF IncMSE (Avg % IncMSE) for Total_prec_fireseason variable: 93.315% IncMSE for Total_prec_nofireseason variable: 179% 2. MLR "lmg" metrics for Total_prec_nofireseason variable: 48.193 "lmg" metrics for Total_prec_fireseason variable: 22.15	Factors influencing fire occurrence identification and likelihood of fire occurrence modeling
Pourtaghi et al. [50]	Boosted Regression Tree (BRT) Generalized Additive model (GAM) RF	Topographical Meteorological Geological data	Accuracies: 1. BRT: 80.74 (with AUC = 0.808) 2. RF: 72.79% (with AUC = 0.7279) 3. GAM: 87.70 (with AUC = 0877)	Forest fires susceptibility maps establishment
Giuntini et al. [54]	DT	Meteorological data	The failures detection results (for a total of 60 events) were about 45% of possible failure identification in the application	Self-organizing and fault tolerance WSN model for forest fire detection

Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the Mean Absolute Percent Error (MAPE). The reported results were as follows: values of 15.85, 4.11 and 51 for the RMSE, MAE and MAPE, respectively with the MLP model, and about 18.35, 4.05 and 54 for the RMSE, MAE and MAPE, respectively with the RBFN. In case of the SVM model, the authors obtained values about 7.33, 3.36 and 69 for the RMSE, MAE and MAPE, respectively.

The deep learning approach [15] is also investigated in forest fires prediction systems, mainly the Convolutional Neural Network (CNN), which is widely employed for this issue. For example, a Deep Convolutional Inverse Graphics Network (DCIGN) was employed for fire spread prediction in the work exposed in Hodges et al. [10]. The authors have studied the forest fire time-resolved spatial evolution prediction. The landscapes, fuel types, and weather conditions (mainly wind) variables were employed in this study. The reported results were 97%, 92%, 93% for the mean precision, sensitivity and F-measure, respectively.

2.1.2. Forest Fires Detection We synthesis in the following the works that deals with the ANNs based forest fires detection systems [16–22]. For instance, Kalabokidis et al. [17] developed the so called Auto-Hazard Pro Decision Support System (AHP DSS), using a combination of multiple data and techniques. They introduced in their system a Fire Risk Index (FRI), which refers to fire risk at specific area due to the human presence. Kalabokidis et al. proposed a system based on existing and improved models, mainly the fire detection module, which is based on the ground-based forest fire detection (FFD) model [23]. The operations center that receives the alarms and images (in demand) use the FFD outputs to make a decision and the fire occurrence confirmation. The system includes 5 modules: weather module (based on an existing high-resolution limited area weather forecasting system (SKIRON)), fire detection module, fire danger module [14], fire propagation module, and resources dispatching module. Kalabokidis et al. introduced the Kalman filtering techniques for the systematic temperature and wind errors deletion, leading thus to improvement in the weather module.

The CNN model is widely employed in fire detection systems mainly for fire presence detection in images [19, 21, 22]. In Zhang et al. [22] the authors proposed a two stages level classifier: the first one was a global image-level testing using a deep CNN and the second one was a fine grained patch classifier (NN model), which was employed to locate the fire patches (if the fire was detected). In this study, two different patch classifiers, namely a linear classifier (SVM) and a non-linear one (the CNN) was compared. Zhang et al. reported accuracies about 92.2% and 93.1% for the SVM-Raw and the CNN-Raw, respectively. Regarding the global image-level testing using a deep CNN (the first stage), a detection accuracy about 90% with a dataset that includes 237 images was reported. A fire detection framework using convolutional neural network based model for the Closed-Circuit television (CCTV) surveillance cameras was developed in Muhammad et al. [19]. The reported results in terms of accuracy, precision, recall and F-measure were about 94.39%, 82%, 0.98 and 0.89, respectively. The used dataset includes 68,457 images. The proposed fine-tuned CNN based fire detection model can process 17 frames/s. In Park et al. [21] a multifunctional AI framework for

Table 3
Summary of Some Studies Regarding Fire Prediction and Detection Systems Based on Other Types of Machine Learning Algorithms

References	Methods	Type of dataset	The main reported results	Tasks
Saputra et al. [73]	Fuzzy logic in WSN	Temperature Humidity CO Smoke	Error ratio: 6.67% (test for 30 sample data)	Fuzzy logic based fire detection and home monitoring system
Chen et al. [72]	MLP Fuzzy logic	Multi-sensor data Temperature Smoke density CO density	Error value = (The proposed system fire probability − The expert probability)^2 Error value: 10^{-4}	Multi-sensors data fusion structure for fire probability prediction
Töreyin et al. [67]	Markov model	11 color videos	Processing time: 10 msec. for images of size 320 × 240.	Flame flicker process modeling using a hidden Markov model (Markov model based flame detection)
Cortez and Morais [57]	SVM	Meteorological data	Predictive results in terms of: MAD: 13.07 RMES: 64.7	Burned area prediction
Manjunatha et al. [70]	Fuzzy logic in WSN	Temperature Humidity Light intensity CO	NA	Data fusion system for fire event detection
Dlamini [60]	Bayesian Belief Network (BBN)	Satellite-based fire dataset MODIS	Recall: 0.963 Specificity: 072 AUC: 0.961	Selection and ranking of biotic, abiotic and human factors that influence forest fires activity

Table 3
continued

References	Methods	Type of dataset	The main reported results	Tasks
Borges and Izquierdo [61]	Bayesian	Vision-based data	False positive rate: 0.68% False-negative rate: 0.028%	Vision-based fire occurrence probability modeling
Bahrepour et al. [62]	Distributed ANN Naïve Bayes	– Wildfire Features included in the Canadian FWI system – Residential fire Temperature Ionization Photoelectric CO gas	Accuracies: Residential fire detection: 81% Wildfire detection: 92%	Data analysis for forest fire and residential fire detection (most contributing factors extraction)
Habiboglu et al. [59]	SVM (RBF kernel)	17 fires videos	SVM (RBF) maximum true detection rate: 96.6% (recall) SVM (linear kernel): 90.9%	Video-based fire detection
Maksimović and Vujovic [55]	Fuzzy Unordered Rule Induction Algorithm (FURIA) One level decision tree (OneR) NN	Several combinations of Temperature Humidity Light and CO	Percentage of correctly classified instances (CCI) 1. FURIA: 87.6% 2. OneR: 71.6% 3. NN: 93.8%	Comparison of data mining techniques on WSN based fire detection system
Saoudi et al. [63]	Naive Bayes	Temperature Humidity Smoke Light sensors	Precision: 94%	Forest fires detection using multi-sensors WSN
Mahmoud and Ren [64]	Rule-based images processing algorithm	Fire Video and fire-like objects video	93.13%: Recall 92.59%: Precision 92.86%: F-score False detection rate less than 40%.	Video-based fire detection

fire detection was proposed. The framework includes several machine learning algorithms (CNN, deep NN and adaptive fuzzy algorithms) and a data transmission delay minimization mechanism, namely a direct-Message Queuing Telemetry Transport (MQTT). Park et al. developed a framework of three blocks: First, the Internet of Thing (IoT) data collection block that collects data (a combination of fire sensors data (temperature, humidity and gas sensors) and image data (cameras)) from heterogeneous sensors. Second, a context preprocessing block, for the image data analysis using a CNN algorithm and sequential data analysis using DNN algorithm. Third, the context decision block, which uses an adaptive fuzzy algorithm for fire probability computation using the results of the context processing block. A Software-Defined Networking (SDN) controller was included in the system for data transfer delay minimization when the fire detection system transmits the data using the MQTT protocol. The reported accuracy was about 95% and the end-to-and delay (data transfer and decision delays) was reduced by 67% in comparison to the legacy fire detection system.

In Maeda et al. [20] the high risk forest fire detection in the Brazilian Amazon area was evaluated using a multilayer feedforward network (MLFN). In this study the NDVI composite Moderate-Resolution Imaging Spectroradiometer (MODIS) data of the year of 2005 was used as dataset to train the MLFN. The approach adopted by Maeda et al. was as follows: the information contained in each pixel of the multi-temporal satellite images are used as inputs to the ANN, then the MLFN assigns values between 0 (lower fire risk) and 1 (higher fire risk) to the considered areas based on the temporal and spectral profile of each pixel. The authors reported a global accuracy about 90% and a Mean Squared Error (MSE) value of 0.07. The particularity of this work was the use of a simple ANN architecture (4 neurons in the hidden layer), which allows a fast training with an acceptable accuracy. A False Alarm Reduction (FAR) system was exposed in Arrue et al. [16]; the system combines infrared-image processing techniques, ANN and rule-based approaches. The FAR system is composed of a sensor interface, an image-processing tool, and a decision function. The information was provided by several sources, namely the visual camera, the infrared camera, meteorological sensors, and the geographical information database. In this study, the ANN was employed to compute forest fire possibility values from the information provided by the infrared-image block. The used ANNs were the BPN, the RBFN and the Dynamic Learning Vector Quantization (DLVQ); this latter is a supervised competitive network. Arrue et al. reported percentages of about 98% for detection possibility and lower than 2% for false alarm possibility (for 517 experiments with false alarms). The reported fire detection rate was 100% (for 51 experiments carried out with fires).

Several studies have been reported in the literature regarding the integration of the ANN models within the WSN for forest fires detection purpose [18, 24–26]. For instance, the MLP model was adopted in Yu et al. [25] for a WSN based forest fires detection system. The MLP model used the data collected from the sensor nodes (including temperature, relative humidity, smoke and wind speed) and produced the weather index at cluster node level. The weather index that estimates the fire occurrence probability will be sent to the manager node via the sink node.

According to this study, the in-networking processing based on the ANN model contributes to the energy saving and thus increases the lifetime of the sensor network. The fire weather index (FWI) was also used in Hefeeda and Bagheri [24]; the authors proposed a WSN for forest fires detection based on the FWI system components, namely the Fine Fuel Moisture Code (FFMC) and the FWI. The detection system was modeled as a k-coverage model. The computed FFMC and FWI values were sent to the processing center for action.

A forest fires multi-criteria detection system using WSN was developed in Liu et al. [18]. The authors evaluated their model based on a multiple layer back propagation ANN with respect to the distance between the sensor node and a fire. Liu et al. reported detection accuracies about 90% (for a distance between the sensor node and the fire of 10 cm) and 40% (for a distance of 20 cm). The TelosB sensor node was used in the proposed prototype. In another work [26], a combination of a multilayer ANN with a multi-sensor WSN for real time identification of a dominant combustion phases has been adopted. Three sensors, namely smoke, CO_2 and temperature were selected among five sensors (CO, CO_2, smoke, temperature and relative humidity) to feed the ANN. The reported results showed that the obtained accuracy with the multiple sensors input was about 82.5% using 1160 data samples. A multiple data sources was also employed in the study reported in Ishii et al. [27]. The authors exposed a fire detection system based on the MLP neural network, with a delay circuit that includes the concept of time. The ANN processes the collected data from three different sensors (temperature, smoke and gas) and generates information about the fire sources heat release rate, and the smoke and gas rates. Authors stated that multiple data sources collected from different sensors reduce the false alarms in contrast to the single sensor data.

In addition to the studies previously mentioned, other works considered the use of the WSN technology for forest fires detection without AI integration, we cite as an example the work exposed in Lloret et al. [28]. This study dealt with the development of a wireless multisensory network system for fires detection in rural and forest area of Spain. The system is based on the Linksys WRT54GL router, multisensors part (the infrared radiation and smoke sensors) and a wireless IP camera. The sensors nodes detect the fire and send an alarm to the monitoring server via a wireless network; using the IEEE 802.11g technology. The firefighter selects the closed IP camera to the sensor node, which sent the alarm, and asks for the real-time images of the suspected zone. The real time visualization allows the firefighter to validate the fire occurrence.

Another new technology such as UAV has been explored for forest fires detection and monitoring [29–33]. The evolution in the development of the UAVs and their technology makes them appropriate for several applications; among them the forest fires monitoring, especially when associated to the machine learning algorithms. The advantage of this approach is the remote sensing that can cover large areas including far away and inaccessible areas. A review of the UAVs types and applications, mainly in forestry applications is addressed in [34].

A platform based on two UAV types (a fixed-wing drone and a rotary-wing drone) for forest fire detection was developed in Kinaneva et al. [32]. The two UAVs involved in this platform detect the data captured by their thermal cameras. The data was processed locally since the UAVs include on board processing units. The two UAVs were connected to the base station to send information about their captures. The model recognizes the smoke in the forest images sent by the UAVs and classifies them by means of the neural network model. In their previous work [35]; the authors used UAVs with fixed and rotary wings in addition to the Long Range (LoRa) digital wireless communication technology (LoRaWAN) sensor networks.

An automatic real-time forest fires detection system based on Unmanned Ariel System (UAS) was presented in Georgiades et al. [30]. The system includes optical and thermal camera. A Robot Operating System (ROS) was used as a chief module for the decision and the peripheral modules automatic detection and control. Similar to the work exposed in Kinaneva et al. [32], Georgiades et al. used a drone in their system for fire detection; the difference was that Georgiades et al. used a single drone whereas Kinaneva et al. used two drones and integrate an ANN in their system for forest images classification. It is noteworthy to precise that the two teams (Georgiades et al. and Hristov et al.) worked on the same project; so called the *Interreg Balkan- Mediterranean project "SFEDA"*.

A muti-UAV-based forest fires detecting and monitoring system was proposed in Sherstjuk et al. [33]. This latter combines a remote sensing, image processing and multi-UAVs. Two types of UAVs were employed, namely fixed-wing micro-UAV for patrolling mission and a rotary-wing micro-UAV for confirming missions. The authors reported about 92% of correct forest fire detection and a processing time less than 2 min.

We sum-up in Table 1 the important outcomes, in terms of the ML type, the used dataset and the main reported results within a set of reviewed studies regarding the ANN based forest fires prediction and detection systems.

2.2. Logistic Regression Based Forest Fires Prediction Systems

The logistic regression [36] is a mathematical modeling approach for events occurrence probability estimation. This approach uses a logistic function to model events that can be expressed in binary mode. It can describe the relationship between several variables to dichotomous variables. A mathematical model of a set of explanatory variables is used to predict a logit transformation of the dependent variable with two values (such as '0' and '1' or 'Yes' and 'No'). Suppose two outcomes of a binary variable: an outcome of '1' with proportion of observations (p); and an outcome of '0' with a probability $(1 - p)$. The ratio of the proportions for the two possible outcomes $(p/(1 - p))$ is called odds. The transformation of the odds using the natural logarithm is called the logit transformation. The logistic regression is widely used in natural events modeling, such as fire modeling by estimating their probability of occurrences. Authors in the work exposed in Chang et al. [37], used a logistic regression to predict forest fires ignition in the Heilongjiang province, China. They employed data including variables such as topography, vegetation types, meteorological conditions, climate, and human activity. The reported global accuracy using the logistic regression was about 85.7%. The effects of different factors (the meteorological conditions, topological, fuel type and human activity) on forest fire occurrences were also addressed in this study. Chang et al. stated that the meteorological conditions including daily minimum temperature, mean wind speed and daily minimum humidity are critical weather conditions of natural forest fire occurrences, in addition to the average mean temperature and precipitation. According to this study, the effect of these factors varies from country to country. For example, in Durango State, Mexico the main driving factors of fire occurrence are: the intensity of land use, land use change, vegetation type and precipitation, whereas in the Mediterranean ecosystem of central Spain the live fuel moisture content is considered as a main factor of fire occurrence. In northeast China, anthropogenic fires are strongly related to indicators of human activity (e.g., proximity to settlements and roads), fuel moisture and vegetation type, which are the most important factors controlling the spatial pattern of lightning fires. The elevation and slope are the factors that affect the forest fires occurrences in eastern Kentucky, USA.

The Geographic Information System (GIS) [38] has also been investigated for forest fires risk map development; mainly in case of the logistic regression model [39–43]. The work exposed in De Vasconcelos et al. [41] is an example of such investigations. In this study a model for wildfire ignition probabilities prediction was proposed. A combination of two algorithms, namely logistic regression and neural network (multilayer feed forward network architecture with a genetic algorithm, used as learning rule) was employed. The study was done in central Portugal, and the data base includes information in a raster GIS. It involved recorded information on date of occurrence, place, country, geographic coordinates, cause of ignition (mainly arson and negligence), land use, and area burned. The total number of final ignition points was 366 observations (242 arson and 124 negligence). The reported maximum accuracies were of about 78.8% (ignition) and 74% (no ignition) for the logistic regression and of about 75.7% (ignition) and 87.8% (no ignition) for the ANN. According to this study, the two methods give acceptable levels of predictive ability.

A logistic regression based model for the spatial patterns of ignitions prediction was exposed in Catry et al. [39]. The authors analysis was based on the human activities and presence factors; and their data includes a set of explanatory variables, namely population density, distance to roads, land cover type and elevation. They also created a Portugal ignition risk map using the logistic regression based model and GIS. The reported accuracies were about 78.2% of correctly predicted ignitions and 82.7% of correctly predicted no-ignitions. Catry et al. claimed that the most influential variable explaining the spatial patterns of ignitions was population density, followed by land cover type, elevation, and distance to roads.

Regarding the spread use of the ANN and the logistic regression as models for forest fires detection and prediction, several comparison studies were conducted [41, 43]. As the work exposed in Vega-Garcia et al. [43], performance comparison of the neural network (back-propagation feed forward network) based human caused fire occurrence prediction against the logistic regression (binary logit model) was addressed in De Vasconcelos et al. [41]. The study area was the Whitecourt Provincial Forest of Alberta and the GIS data was employed in this investigation. It was revealed that compared to logistic regression approach, the

ANNs are more complex and are considered as black boxes, thus forest managers prefer a simple procedure such as a regression analysis. However, the serial correlations in the data present a constraint for the regression analysis, whereas the ANN has advantage over the statistical methods since its performance is not altered by high correlations among the input variables (such as geographical and temporal variables). According to this study, the two methods reached comparable accuracies. The reported accuracies for the ANN based model were about 85% (correctly predicted no-fire) and 78% (correctly predicted fire). However, De Vasconcelos et al. claimed that their model presents limitations, mainly the high number of false alarms and the fact that the model cannot give prediction for days outside the fire season period.

In Padilla and Vega-Garcıa [44], the logistic regression method was used for the probability of human-caused fire occurrence modeling. The study area was divided into 5 ecoregions in Spain. The data used in this study comprises a daily weather data, geographic characteristics and historical records of daily fire occurrences between 2002 and 2005. The variables used in this study include the commonly used fire weather indices of the Canadian forest fire weather index system [45]. It was concluded that the FWI was within the three most important variables, the FFMC was also a significant variable. The performance evaluation results for the 53 models showed that the total percentage of correctly predicted fires was in range of 47.4% to 82.6% (from 0.52 to 0.86 for the Area Under RoC Curve (AUC) value).

2.3. Decision Tree and DT Ensembles Based Forest Fires Prediction and Detection Systems

Decision tree [46] is a supervised learning algorithm, known as an Iterative Dichotomiser (ID3) developed by J. Quinlan; he later presented the second learning algorithm C4.5. The third learning algorithm of the decision tree is the Classification and Regression Tree (CART), which was proposed by L. Breiman et al. [47]. The CART algorithm combines classification and regression. The decision tree algorithm allows predicting, explaining and classifying outcomes. The result is a tree structure, where the internals nodes represent the tests on attributes, branches represent outcomes of the test and leaves represent the class labels (decisions). The root node is the most significant attribute or split. The possibility to translate the obtained tree into a set of IF-ELSE rules makes the DT understandable and easy to use. The DT algorithm is employed as a single tree or as ensemble algorithms based upon multiple decision trees to improve predictions. The DT ensembles are mainly the Boosting DT, the Bagging DT and the Random Forest (RF) [48] algorithms. Decision tree learning algorithm and its ensembles have been successfully used for the purpose of decision making. They have been widely applied to several domains due to their robustness to noise, ability to deal with redundant attributes and good generalization ability. The potential applications of these methods in ecological issues are numerous; they are also explored in forest fires prediction and detection issues.

2.3.1. Forest Fires Prediction Stojanova et al. [49] is an example of works that have adopted the DT and its ensembles approach to predict forest fires. Stojanova et al. evaluated the forest fires occurrence in Slovenia using the decision tree and its ensembles in addition to the logistic regression model. The authors used three datasets, namely GIS data, multi-temporal MODIS data and meteorological ALADIN (Aire Limitée Adaptation dynamique Dévelopment InterNational) data. According to this study the bagging DT gives the best results in terms of accuracy, precision and Kappa statics in case of the continental Slovenia dataset. The reported accuracies were about 81.2%, 84.9% and 84.4% for the DT, the bagging DT and the boosting DT, respectively. The same authors addressed a study for fire outbreaks risk estimation [50]. They drew a comparison of predictive performance of several data mining techniques, and concluded that the best performances were obtained with the DT ensembles.

In Pourtaghi et al. [51], three forest fires susceptibility maps were proposed using three machine learning methods, namely the Boosted Regression Tree (BRT) (a combination of regression trees and boosting DT), the Generalized Additive Model (GAM) and the RF. The three models were evaluated using topographical, meteorological and geological data in the Minudasht Township, Golestan Province, Iran. Pourtaghi et al. constructed their fire locations and occurrences dataset from the MODIS satellite images, historical records and national reports. The reported prediction accuracies for the three forest fires susceptibility maps were about 80.74%, 72.79% and 87.70% for the BRT model, the RF model and the GAM model, respectively. According to this study, annual rainfall, slope degree, distance to roads, land use and annual temperature were the most influencing factors in forest fire occurrence.

The study discussed in Oliveira et al. [52] exposed two models based on the Multiple Linear Regression (MLR) and the random forest for factor influencing fire occurrence identification and likelihood modeling in the European Mediterranean region (Portugal, Spain, France, Italy and Greece). The authors compared the two models in terms of predictive ability and the variables selected by each method. The comparison showed that the RF model presents a higher predictive ability than the MLR; this is due to the fact that the non-linear relationships between the variables are not assumed by the MLR. Nevertheless the MLR showed a positive relationship between the dependent variable and the predictors. In this study, the mean decrease in accuracy (IncMSE) was used as variable importance measure in the RF model, the reported results were: 93.31% (Avg % IncMSE) for the Total_prec_fireseason variable and 179% for the Total_prec_nofireseason variable. Whereas the percentage of the "*lmg*" metrics is used in the MLR model variables selection, the reported results were: 48.19 for the Total_prec_nofireseason variable and 22.15 for the Total_prec_fireseason variable. The results of this study showed that among the eight variables used in each method, the off-season precipitation was the most important variable for both models.

The Classification and Regression Tree (CART) algorithm was evaluated for modeling the probability of fire occurrence in Lozano et al. [53]. The authors developed special models of fire occurrences at different spatial observation scales.

Several environmental factors were considered in this study, such as the vegetation status and type, accessibility, fire history and topography. The landsat imagery was used for the vegetation status estimation. Lozano et al. reported an overall accuracy of 88.39%. Besides forest fires prediction and detection issues the statistical methods, namely Regression Tree Analysis (RTA), Bagging Trees (BT), RF, and Multivariate Adaptive Regression Splines (MARS) were applied in the context of ecological prediction (predictive biological mapping). For instance, Prasad et al. [54] proposed the trees species distributions prediction in the eastern United States under multiple climate conditions.

2.3.2. Forest Fires Detection It is noteworthy to precise that the DT algorithm and its ensembles are mostly used for the fire prediction purpose rather than detection (as for the logistic regression). Few studies were reported in the literature regarding the DT based forest fires detection systems. For example the DT algorithm was integrated in the WSN based FFD system exposed in Giuntini et al. [55]. The authors proposed a self-organizing and fault-tolerant (at the application level) WSN model for wildfire detection. The forest fires dataset of the UCI machine learning repository was used for the evaluation of three decision trees components included in the model. The decision tree algorithm was also investigated in the work discussed in Maksimović and Vujović [56]. This study exposed the data mining (including the DT algorithm) techniques in WSN based fire detection system. Maksimović and Vujović stated that a classifier such as the one-level decision tree (OneR) give acceptable results in case of small dataset.

The main reported results within a set of studies reviewed in this paper, regarding the forest fires prediction and detection systems based on the logistic regression and DT and its ensembles are summarized in Table 2.

3. Additional Types of Machine Learning Algorithms for Forest Fires Prediction and Detection Systems

Apart from the mostly used ML algorithms for forest fires prediction and detection (ANNs, logistic regression and DT), other types of ML algorithms have been investigated for this purpose. We expose in this section a number of forest fires prediction and detection systems based on other methods, such as the SVM, the Bayesian and the fuzzy logic models.

3.1. SVM Based Forest Fires Prediction and Detection System

A support vector machine [57] based solution for burned area prediction was discussed in Cortez and Morais [58]. The authors used the meteorological data from the northeast region of Portugal. The dataset includes, weather variables, namely temperature, rain, relative humidity and wind speed. It was concluded that the SVM based solution is suitable for small fire detection and presents a limitation for large fires. The Mean Absolute Deviation (MAD) and the Root Mean Squared (RMSE) global metrics were used to the overall performance computation, authors reported values about 13.07 and 64.7 for the MAD and the RMES, respectively. The SVM model is also adopted in Özbayoğlu and Bozer [13] for burned forest area identification. The authors obtained values about 7.33, 3.36 and 69 for the RMSE, MAE and MAPE, respectively. A video-based fire detection system that uses a region covariance matrix approach [59] was proposed in Habiboglu et al. [60]. The SVM algorithm (Radial Basis Function (RBF) kernel) was used as a classifier of a dataset that includes seven positive and ten negative videos. The SVM model (RBF kernel) allows a maximum true detection rate about 96.6%, and about 90.9% with the linear kernel. According to this study, the proposed temporally extended covariance matrix method, which combines color, spatial and temporal information can process 20 frames (320×240 frames) per second.

3.2. Bayesian and Markov Models Based Forest Fires Detection Systems

A Bayesian Belief Network (BBN) model was developed in Dlamini [61] for the selection and ranking of biotic, abiotic and human factors that influence wildfire activity in Swaziland. The satellite-based fire dataset, namely the MODIS active fires in Swaziland from 2001 to 2007 was employed for the BBN evaluation. Dlamini reported values of about 0.96, 0.72 and 0.96 for the sensitivity, the specificity and the AUC, respectively. He concluded that the most influencing factors in the wildfire occurrence in Swaziland were (in order of influence) the land cover, elevation, mean annual rainfall and mean annual temperature. The vision-based sensors are widely used for environmental issues as alternative to the existing sensors (alarm sensors, infrared, ion and optical sensors). For instance, a vision-based (a color-based) fire occurrence probability modeling was proposed in Borges and Izquierdo [62]. Borges and Izquierdo considered a Bayesian classifier in their study; they evaluated the change of several features (color, area size, region coarseness, boundary roughness and skewness). The analysis results were used by the Bayes classifier for fire occurrence determination in video frames, the reported false positive and false-negative rates were about 0.68% and 0.028%, respectively. The authors assessed that their model is suitable for real time fire detection and also for automatic newscast videos events retrieval. The work exposed in Bahrepour et al. [63] discussed a dataset analysis to extract the most contributing features for wildfire and residential fire detection using data mining approaches in WSN. The reported accuracies using the distributed neural network and the naive Bayes were about over 81% for residential fire detection and over 92% for the wildfire detection. The naive Bayes classifier was also adopted for forest fires detection in Saoudi et al. [64]. This study targeted the data size reduction in a multi-sensors (temperature, humidity, smoke and light sensors) WSN. Saoudi et al. obtained a precision about 94% for the naive Bayes.

The vision-based systems associated with image processing techniques have been also employed as fire detection systems [23, 65]. A combination of image processing techniques (movement containing region detection based on background subtraction and color segmentation) for a video based fire detection model was discussed in Mahmoud and Ren [65]. The proposed color model was based on YCbCr color space and temporal variation to correctly detect fire and avoid other moving object (e.g. trees, animals, bird…) detection after background subtraction. Mahmoud and Ren tested their algorithm on a dataset including 6 video (4 fire videos and 2 fire-like objects videos). The reported performances were about 93.13%, 92.59% and 92.86% for recall, precision and F-score, respectively. A false detection rate less than 40% was obtained in this study. In Breejen et al. [23] the authors proposed an autonomous forest fires detection system installed on a small platform in a tower. The system (ground-based) is based on the temporal difference of the smoke plume with the natural background. Breejen et al. used four staring black and white video cameras. The processing was performed locally at the tower; the alarm is the only sent information to the operational center to limit the bandwidth; other information such as images were sent on request. The drawback of this technique is the cost and complexity of such system since a great number of cameras is needed for a large-scale forest fire management.

Even a Markovian approach [66] has been explored by researchers for fire detection modeling [67–69]. A Markov model based fire detection system was presented in Töreyin et al. [68]. The authors discussed a flame flicker process modeling using a hidden Markov model. In fact the pixels in flame boundaries vary rapidly and randomly, this characteristic makes the Markov model more suitable for modeling this process. Töreyin et al. proposed a three state Markov model for flames detection in color video. Temporal and special analysis of flame and non-flame pixels were performed by the developed model; two states for color variation within a flame (flame moving pixels) and one state for non-fire colored pixels. The results of the experiments conducted using 11 videos showed that the Markov model reduces the number of false alarms compared to methods based only on color information and motion detection. The authors reported a processing time about 10 msec. for an image of size 320×240.

3.3. Fuzzy Logic Based Fire Prediction and Detection Systems

The fuzzy logic approach is introduced by Zadeh [70]. This approach is employed with uncertain and vague data. It is an alternative to the classical logic where the variable truth values are only integer ‘0’ or ‘1’, whereas the truth values in the fuzzy logic are real values between ‘0’ and ‘1’. This approach has been applied in many fields, such as forest fires detection and modeling [56, 71, 72] and residential fire monitoring [73, 74]. In Saputra et al. [74], a fuzzy logic based system for fire detection and home monitoring using WSN technology was proposed. The collected data from a unit that combines four sensors, namely temperature, humidity, CO, and smoke was used for fire probability value computation based on the fuzzy rule method. The output value given by the fuzzy rule was used for sleep mode setting to reduce power usage in the sensor node. The reported error ratio was about 6.67% for a test performed for 30 sample data. In the case of fire prediction, a hybrid model that combines a multi-layer neural network (3-layers BP NN) and a fuzzy logic approach was proposed in Chen et al. [73]. The model was applied in a multi-sensor data fusion structure that includes three layers, namely the signal layer for multi-sensor data collection (temperature, smoke density and Carbon Monoxide (CO) density), the characteristic layer; this layer includes two units, namely the neural network pickup unit (NNPU) and the expert-database pickup unit (EDPU). The third layer is the decision layer where the data-fitting characteristic (probability) extracted by the NNPU and the experiential characteristic extracted by the EDPU were fused by the fuzzy inference system to predict the fire probability. The fusion technique applied in multi-sensors data processing allows communication activity minimization and energy saving.

In another work [71], the authors investigated the same approach as [74]. Manjunatha et al. proposed a data fusion process using a fuzzy rule based system at cluster head level. The system fuses the data collected by 4 sensors (temperature, humidity, light intensity and the amount of CO) and identifies the event. According to this study, the multiple data fusion technique minimizes the communication cost and false alarm. In Maksimović and Vujović [56], a comparison study of various data mining techniques in WSN based fire detection system was presented. According to this study, the prediction is better when using the neural network classifier in the case of larger dataset, whereas in the case of small dataset, classifiers such as the one-level decision tree (OneR) or Fuzzy Unordered Rule Induction Algorithm (FURIA) give reasonable results. The authors stated that the selection of an appropriate data mining algorithm depends on the application and the compatibility of the observed dataset.

As for Sect. 2, we sum-up in Table 3, the important outcomes, in terms of ML type, used dataset and the main reported results within a set of studies regarding fires prediction and detection systems based on other types of machine learning algorithms apart from ANNs, logistic regression and DT.

4. Discussion

Before discussing the important outcomes within each study, we discuss the factors influencing the fire ignition occurrence. The assessments of factors influencing fire occurrence and risk have been considered in several studies resumed in this paper (e.g. [14, 37, 52]). The main and critical factors in fire ignition and spread are meteorological (temperature, relative humidity, precipitations and wind speed) and climatic conditions. In addition to meteorological elements, the topological and vegetation types are also influencing factors, which are mainly considered in fire risk map development. Even social conditions (human causes, negligence or arson) are taken into consideration when assessing the fire risk and causes. These factors constitute the datasets used for the machine learning based forest fires prediction and detection models training. For example the GIS data that has been investigated for forest fires risk maps development, mainly when adopting the logistic regression algorithm as a model.

Considering the study addressed in Oliveria et al. [52] the factors and conditions influencing fire occurrences operate differently depending on the regions. This is due mainly to the environmental and social conditions, which differ from country to country. It is also due to the studied area and the ecosystem of each country. According to the work reported in Chang et al. [37], the intensity of land use, vegetation type and precipitation variables are the main influencing factors in fire occurrence in Durango State, Mexico. The live fuel moisture content is the principal factor of fire occurrence in the Mediterranean ecosystem of central Spain. In northeast China, anthropogenic fires are strongly related to indicators of human activity, fuel moisture and vegetation type. In case of the eastern Kentucky, USA, the elevation and slope are the most factors that affect the forest fire occurrences. According to [61], the most influencing factors in the wildfire occurrence in Swaziland are (in order of influence): the land cover, elevation, mean annual rainfall and mean annual temperature.

The assessment of factors influencing fire occurrence and risk was also investigated in Vasilakos et al. [14]. According to this study, the most influencing variable in regard to the weather conditions is the rainfall in the last 24 h followed by temperature, wind speed, and relative humidity. The reported percentage of influence of these weather conditions in the fire weather index were about 35.9%, 28.7%, 20.9% and 14.5% for the rainfall, temperature, wind speed, and relative humidity, respectively. The two most significant variables regarding the fire hazard are the 10-h fuel moisture content and fuel models. The month of the year and proximities to urban areas, are the most influencing variables in the fire risk index with respect to human presence and socioeconomic impacts.

Regarding the machine learning based forest fires prediction and detection models reviewed in this work, a multiplicity of ML approaches have been adopted and investigated in the context of fire prediction and detection. The neural network model is widely employed, particularly the supervised ANN, such as the multi-layer NN [16, 20, 25] for forest fires detection purpose and [9, 13, 41, 43] for prediction purpose. The reported accuracies with the multi-layer neural network varied from 65% to 87.9%. It is noticeable that the other types of ANN (unsupervised ANNs), such as Kohonen, SOM and Hopfield models are not investigated in the forest fires prediction and detection systems.

It is worth noting that the deep ANN, mainly the conventional neural network has recently been applied for fire modeling. This approach is adopted for fire presence detection in images [19, 21, 22] and fire spread prediction [10]. The CNN and the deep neural network gave the best accuracies that range from 90% [22] to 94.39% [19]. The deep neural network is a promising approach for forest fires prediction and detection. This ML model showed an acceptable predictive ability and presented good accuracies.

The second most used machine learning algorithm for forest fires modeling is the logistic regression [37, 39, 41, 43, 44], which is mainly employed in studies that use the GIS data in the wildfire ignition probability prediction. Vega-Garcia et al. [43] and Padilla and Vega-Garcıa [44] treated the probability of human caused fire occurrence modeling. A maximum percentage of correctly predicted fire of 82.6% was reported by Padilla and Vega-Garcıa [44]. The reported accuracies with the logistic regression varied from 74% to 85.7%.

Considering the spread use of the ANN and the logistic regression models in the forest fires prediction and detection systems, several comparison studies were conducted (e.g. [41, 43]). The maximum accuracies reported by De Vasconcelos et al. [41] were of about 78.8% (ignition) and 74% (no ignition) for the logistic regression based model and of about 75.7% (ignition) and 87.8% (no ignition) for the ANN based model. The comparisons of the ANN model against the logistic regression showed that the two methods give comparable accuracies and acceptable levels of predictive ability. Nevertheless, each model has its advantages and limitations. The comparison made in Vega-Garcia et al. [43] showed that the ANN is more complex compared to the logistic regression; however, this latter presents a limitation for the data that present a serial correlation. In opposite, the ANN based model performances are not altered by high correlations among the input variables such as geographical and temporal variables. On the other hand, the robustness of the ANN model makes it adaptable to the unpredictable non-linearity and variability of the data related to natural phenomena, such as forest fire as stated by Dimuccio et al. [9].

The decision tree learning algorithm and its ensembles, namely the Boosting DT, the Bagging DT and the RF algorithms are also applied in forest fires prediction and detection systems. The DT is suitable for this purpose due to its simplicity and ease of readability compared to other machine learning algorithms. The reported accuracies [49] for the DT and its ensembles are about 81.2% (simple DT), 84.9% (Bagging DT) and 84.4% (Boosting DT). The comparison reported in Oliveira et al. [52] indicated that the random forest model showed higher predictive ability than the Multiple Linear Regression (MLR). This is due to the fact that the non-linear relationships between the variables are not assumed by the MLR. The CART algorithm is also used for fire modeling, accuracy around 88.39% was observed in Lozano et al. [53].

Besides forest fires prediction and detection issues the potential applications of the DT ensembles (RF, BT) are numerous. They can be used in the predictive biological mapping, target locations or probability surfaces for common, rare, or invasive species (plant or animal) identification, nutrient concentrations across a landscape and map pollution levels as reported in Prasad et al. [54].

Besides the mostly used machine learning algorithms in fire modeling (ANN, logistic regression, DT and its ensembles), additional ML algorithms have been considered, such as the SVM, the Bayesian, the Markov model and the fuzzy logic. The fuzzy logic is mainly employed for data fusion in multi-sensors data (multi-source data) when considering the WSN based forest fires detection systems. Regarding the SVM based models, a maximum true detection rate of about 96.6% was obtained in Habiboglu et al. [60], and an accuracy about 92.2% was reported in Zhang et al. [22]. In the case of the naive Bayes model about 94% precision was observed as reported in Saoudi et al. [64]; and a sensitivity value about 0.96 is reported in Dlamini [61]. It is noticeable that the SVM model is not widely employed, even though it gives good result in terms of true detection rate. This is due to the fact that this approach is suitable for small fire prediction and has limitation (lower predictive accuracy) in case of large fire according to the study reported in Cortez and Morais [58].

When considering the WSN integrating machine learning methods for forest fires detection, it is shown that the use of multi-sensors based WSN system gives a better accuracy compared to the single sensor based WSN system [26]. According to the reviewed works that applied the fuzzy logic as fire prediction and detection models; the fuzzy logic approach is mainly used in the multi-sensors WSN for data fusion. Data fusion process ensures the reliability and accuracy of the sensed information and thereby minimizes the communication activity and false alarms rate. Manjunatha et al. [71] claimed that the multiple data fusion process minimizes the communication cost and false alarms. A previous study conducted by Ishii et al. [27] also explained that the use of multi-sensors data in a neural network based model can reduce the false alarms caused by transient variation of a single sensor output.

In the next paragraphs, we regroup and discuss the reviewed works according to the specific task (e.g., the vision-based forest fires detection, ignition prediction, human-caused fire occurrence prediction and modeling...) independently of the adopted ML types. One of the widely discussed issues in the context of the forest fires detection purpose is the vision-based fire detection using fire images or fire videos. The studies reported in [19–22] dealt with this issue. A global accuracy about 90% was obtained with the MLFN based fire detection model using multi-temporal satellite images [20]. The forest fires detection using a deep CNN was investigated in Zhang et al. [22]. The authors reported detection accuracy about 90% for the global image-level testing using a deep CNN and accuracies about 92.2% (with the CNN classifier) and 93.1% (with the SVM classifier) for the fire patches location. The reported results in terms of accuracy in Muhammad et al. [19] that also used the CNN model for fire detection using the CCTV surveillance camera images was about 94.39%. Park et al. [21] adopted a combination of multiple AI framework that includes the CNN (for the image data analysis), the deep NN (for sequential data analysis) and the adaptive fuzzy logic (for fire probability computation (decision)) algorithms. They reported accuracy about 95%. It is noticeable that the CNN is widely used for the fire detection in images; the combination of CNN with others MLs such as the SVM and the fuzzy logic enhances the performances of such system and reduces the end-to-and delay (data transfer and decision delays) in comparison to the legacy fire detection systems [21].

The video-based fire detection systems [60, 62, 65, 68] were investigated using various ML models. According to Habiboglu et al. [60] the SVM model allows a maximum true detection rate about 96.6% and can process 20 frames (320×240 frames) per second when employed as a video-based fire detection model. The flames detection in color video using the Markov model based fire detection system was presented in Töreyin et al. [68]. It was assessed that the Markov model reduces the number of false alarms compared to methods based only on color information and motion detection. The authors reported a processing time about 10 msec. for an image of size 320×240. Values of about 0.68% and 0.028% were obtained for the false positive and false-negative rates, respectively; when using the Bayesian classifier in a vision-based fire occurrences probability model [62]. In another work Mahmoud and Ren [65] reported performances about 93.13%, 92.59% and 92.86% for recall, precision and F-score, respectively. And a false detection rate less than 40%.

The probability of human-caused fire occurrence prediction and modeling has been treated in [37, 43, 44, 61]. The logistic regression model was used in ([37, 43, 44], the ANN model was also used in this work) whereas a Bayesian belief network based model was developed in Dlamini [61]. The logistic regression allows a maximum percentage of correctly predicted fire of 82.6% [44] and a global accuracy about 85.7% [37]. A percentage of correctly predicted fire using the ANN was about 78% [43]. Dlamini reported a value about 96% for the correctly predicted positive cases. It is noticeable that the Bayesian model allows a good sensitivity, i.e. correctly predicted positive cases [61], followed by the logistic regression than the ANN (RBPN). Catry et al. [39] also investigated the human activities and presence factors in their logistic regression based model for the spatial patterns of ignitions prediction. The reported global accuracy was about 79.8% (78.2% of correctly predicted ignitions and 82.7% of correctly predicted no-ignitions). It is revealed that population density was one of the most influential variable explaining the spatial patterns of ignitions.

The WSN technology for real time fire detection with AI integration [25, 26, 64, 71, 74] has been widely considered. It is noticeable that the ANN models (mainly the MLP model) are widely adopted when considering the WSN based fire detection system. The MLP model was used for the in-networking processing for energy consumption saving [25]. It was also employed for real time identification of a dominant combustion phases [26], the obtained accuracy was about 82.5%. The fuzzy logic model was also adopted for fire probability value computation. The reported error ratio was about 6.67% for a test performed for 30 sample data [74]. In Manjunatha et al. [71] the fuzzy logic was employed to minimize communication cost and false alarm. The naive Bayes classifier was investigated in forest fires detection using multi-sensors WSN; it allows a precision about 94% [64].

It is important to notice that the SVM, the Bayesian, the Markov and fuzzy logic algorithms are less employed compared to the ANN and logistic regression models.

5. Conclusions

We surveyed in this paper various methods and approaches proposed for forest fires prediction and detection systems. The reported works in the literature show that the machine learning algorithms are widely used for the forest fires prediction and detection purposes. Researchers paid more attention to the integration of the artificial intelligence in the forest fires modeling, mainly in WSN and UAV based forest fires monitoring systems.

According to the reviewed studies, the neural network and logistic regression based approaches for fire prediction and detection have been widely used. The mostly employed ANN model is the supervised multi-layer ANN as a single unit or integrated in WSN based fire monitoring systems. As assessed in several works, the use of multi-sensors data in neural network based forest fires detection model can reduce the false alarms caused by transient variation of a single sensor output. Moreover, the multiple data fusion process minimizes the communication cost and saves the energy.

In recent studies, the deep ANN (mainly the CNN) has been explored for fire modeling; it is revealed that the deep neural network is a promising approach for this issue. According to the reviewed works, the CNN and the deep NN give very acceptable accuracies.

In addition to the mostly used machine learning algorithms in forest fires prediction and detection, namely the neural network, the logistic regression and the DT and its ensembles, other types of machine learning algorithms have also been investigated, such as the SVM, the Bayesian and the fuzzy logic; however, these models are less employed in comparison to the ANN and logistic regression models.

We consider that the present paper is meant to help researchers to have an overview of the state-of-the-art in forest fires prediction and detection systems that still represent an open issue. The development of advanced systems that integrates the artificial intelligence in such systems is a very promising direction that predicts such critical environmental issue and support public policies in the control of forest fires; on the other hand, it facilities the firefighting task to mitigate the forest fires threat.

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