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A Review of Wildfire Studies using Machine Learning Applications

Nur Farhana Abdul Aziz[1], Norsuzila Ya'acob[1,2,*], Azita Laily Yusof[1,2], Murizah Kassim[1,3]

[1] School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia
[2] Wireless Communication Technology (WiCoT), School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia
[3] Institute for Big Data Analytic and Artificial Intelligence (IBDAAI), University Teknologi MARA, 40450 Shah Alam, Malaysia

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ABSTRACT

Machine Learning (ML) is a subset of Artificial Intelligence that was used in environmental science and management for more than 30 years. Neural Network is a well-known and leading model where ML is being practiced. Recently, ML has become one of the influence tools in medical, medicine, agriculture, environment, and wildfire applications. Thus, making it exceptional when deciphering various problems. This paper has reviewed the implementation of ML techniques in wildfire incidence because it is a very complex process and it very essential to have knowledge, understanding, and awareness for handling it. In this paper, the overview of ML is generally described while the chosen and popular ML method among wild applications since 1990 are defined in detail. The use of the ML methods in wildfire applications is analysed into four categories, which are Fire Detection, Fire Mapping, Fire Occurrence Prediction, and Fire Susceptibility Mapping. Overall, about 109 related publications are identified within the study area and are located all around the world using numerous ML methods consisting of Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN), Bayesian Networks (BN), Naïve Bayes (NB) and Maximum Entropy (MaxEnt). Nevertheless, expertise in ML and wildfire science are essential to provide a good and realistic result along the process of modelling ML.

1. Introduction

Wildfire is a well-known global phenomenon causing major deforestation and loss of wildlife habitat thus resulting in many species extinction [1]. Fire had helped people to form landscape structures and designs that develop a new ecosystem by changing several aspects such as plant growth, soil nutrient and biological diversity [2]. Wildfires play a crucial role as a natural process that introduces an ecological cycle and keeps up ecosystem sustainability. On the other hand, in the preliminary phase of forest generation, wildfire work as a main ecological process where it gives a powerful effect on young trees' growth, dispersion, and germination of seeds [3]. Moreover, the substance turnover, energy flows, forest age, species structure, and landscape formation are also influenced by wildfire activity [4].

* *Corresponding author.*
E-mail address: norsuzila@uitm.edu.my

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In natural conditions, high air content in peat swamp forests makes it difficult to burn, but some activities can change peat swamp conditions to dry, and flammable as well as speed up the rated its spread. The reasons these wildfires can occur are linked into two categories: human factors and natural factors [5]. Globally, nearly 420 million hectares were estimated as an annual burned area [6] or larger than India [7]. Based on previous reports and research, more than 90% liability on humans for the fire ignition, and the rest is due to lightning factor. Based on Forest Fire Management Plan by Selangor Forestry Department, the reason wildfire happened are arson, former log trenches, power lines, illegal logging for agriculture, excessive drainage outside the forest, illegal drainage near the forest, drainage for control the fire, development area, lightning, camping fire, stubble burning and others [8].

In times of severe droughts, wildfire incidents may bring about a huge annihilation of forest benefits and can also cause transboundary pollution that may across other states, or the worst is across the country. Biomass ablaze after wildfires is recognized as a major supplier of aerosols, carbon fluxes, and trace gases, which infect the atmosphere and devote to radiative that is accountable for global climate changes [9]. This phenomenon affects people directly or indirectly. Moreover, climate change also has a negative impact on the economy and health of the country. Therefore, billions of dollars are used up every year on fire management activities to reduce and prevent wildfire's negative effects.

Wildfires have caused considerable losses in global forest resources and people's lives and properties, seriously impacting the global ecological balance, and have received considerable attention from countries worldwide. Wildfires have caused plenteous losses to ecologies, societies, and economies. To diminish these losses due to wildfires, modeling and forecasting the existence of wildfires are significant because they can help to prevent wildfires and at the same time manage the forests.

Wildfire is a very complex process and it is important to have knowledge, understanding, and awareness, to handle wildfire with a structured wildfire management plan. It was formed based on emergency disaster management with response to human and natural disasters. The four main components of the fire disaster management cycle are prevention, preparedness, response, and recovery [8]. Fire disaster management nowadays is necessarily important as an essential tool to predict, prevent, prepared, and respond the wildfire incident [10]. At present, most fire risk models are constructed using a wildfire database. The use of satellite images and GIS is known as a significant advance and is prominent in the model formation [11] in monitoring and observing wildfires.

Currently, active fire data are reachable through online repositories enabling the user to access the information at any moment [12]. Recently, new sensors were amalgamated into Earth International Programs to reach new goals and improved the techniques in wildfire application [13]. Each satellite has its useful specialties, and users can apply depending on their applications. NASA, TERRA, AQUA, and GOES (Geostationary Operational Environmental Satellite) are involved with fire detection sensors. While Advanced Very High-Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), Visible Infrared Imaging Radiometer (VIIRS), and Landsat series surround with sensors that specialized in monitoring vegetation dissemination and changes. Moreover, the amelioration of weather and climate prediction simulations or models is used to enhance extreme fire weather prediction [14]. Contemporaneously, the empirical and statistical model of wildfire occurrences can boost the accuracy of predictions.

In addition, the appeal of Artificial Intelligence (AI) and Machine Learning (ML) usage in environmental applications has seen a rapid uptake in the last decade. The research that involved ML methods includes flood forecasting [15], water resources [16,17], water prediction [18], forest ecology [19], earth system science [20], geoscience [21], overcoming climate change [22], and geoscience and remote sensing [23] are examples and proved that ML has been growing used in many applications recently. There are a few ML algorithms that have been used in this application such as Decision Trees (DT) [24], Neuro-Fuzzy (NF) [25], Artificial Neural Networks (ANN) [26], Genetic Algorithm (GA) [27], Bayesian network (BN) [28], Maximum Entropy (MaxEnt) [29], Random Forest (RF) [30], Support Vector Machines (SVM) [31,32], Naïve Bayes (NB) [33], etc.

2. Remote Sensing & Geographical Information System (GIS)

Remote sensing is a technique for collecting data or information about the earth without taking physical contact or taking samples of the earth's surface. It is also known as a technology that uses a sensor on a platform at a distance away from the object. A sensor is used to measure the energy reflected from the earth. Then, it will transfer to the receiving ground station to be processed and come out as information in the form of a digital image or as a photograph. The sensor is equipped on a satellite orbiting the earth, airborne structure, or on a plane [1,2]. There are many applications of remote sensing, including earth monitoring, land use or land cover mapping, environmental pollution, and urban planning.

As reviewed previously, remote sensing methods turn out to be more affordable and can act as data suppliers in real or near real-time. This data can be managed to create and fit with ML over time. In addition, ML can be applied to explore sensor data. For example, GIS and remote sensing techniques are used in wildfire-induced Natural Hazard Triggering Technological Disasters (Natechs) risk assessment [3], and in Mediterranean France, space-time structures of wildfire occurrences are modeled using Bayesian Network with applied remote sensing and GIS data [4]. Remote sensing data is important in image classification applications [5]. Image classification is a crucial role in wildfire risk analysis.

Wildfire gives a big impact on the environment especially on vegetation index [6], soil characteristics [7,8], and hydrology systems with increased runoff and decrease soil filtration [9,10]. In wildfire applications, remote sensing can offer results of risk spreading [11,12], and hotspot detection [13–15] by modeling the thermal parameters and mapping the affected areas [16–18] besides can come up with the real-time results. To predict the fire existence, many factors need to be considered. Such as economy, social and human activities. However, these factors are unrelated to remote sensing studies.

Generally, GIS is beneficial to produce and create new information and make decisions in many applications including air, water, health, crime, etc. [19]. There is no special regulation on wildfire and forest fires. However, there is a foundation forbidding fire-related activity in the permanent reserve forests and there are punishments for such crimes [20].

3. Artificial Intelligence (AI) and Machine Learning (ML)

ML is a subdivision of AI that concatenates on creating predictive, informative, or implemented models to solve the problem by accumulating data or information about the problem. ML algorithm comes out with its internal model from the collected data. The wildfire prediction method has their own parametric rules straight from the data. Additionally, it contains huge and complex parameters number, which is very valuable and beneficial [21]. Hence, ML approaches can be recognized as one of three categories: supervised learning; unsupervised learning; or semi-supervised learning.

3.1 Supervised Learning

Supervised learning is where the input variables *(x)* and the output variable *(Y)* are known, however the algorithm is used to understand the whole parameterized function, *Y = f(X)*. The purpose of supervised learning is to evaluate the function of the parameter using existing data correctly. Therefore, a new input variable *(x)* can foretell the output variables *(Y)* for those parameters of the function. This category is the most effective and popular ML method also known as the simplest forms [22].

3.2 Unsupervised Learning

Unsupervised learning is where relationships or patterns are extracted from the data without any guidance as to the "right" outcome because only input data *(X)* is known while the output variables are unknown. Unsupervised learning is different from supervised learning. It has no correct outcome. So, the purpose of unsupervised learning is to create the basic structure of the model or method to understand more about the data [21]. The algorithm was created to discover and introduce the data structure. These are called unsupervised learning because unlike supervised learning there are no correct answers and there is no teacher. Algorithms are left to their own devices to discover and present an interesting structure in the data.

3.3 Semi-Supervised Learning

Semi-Supervised Learning is blend between supervised and unsupervised learning because the input data has unfinished information about the target variable. Numerous machine learning faced these difficulties and fall into this category since the target variable is expensive or time-consuming as it may need expertise [21]. To overcome this, unsupervised learning methods can be applied to learn and understand the arrangement of the input variables. Besides, the supervised learning methods can be used to calculate the predictions for the unlabeled data and apply the supervised learning algorithm as training data, and the method is applied as a prediction for new invisible data.

Machine learning is an approachable method that can learn and develop from familiarity devoid of being complex programmed. Recently, numerous researchers used Machine Learning (ML) because it has shown tremendous potential in research recently. The probability that is built from Machine Learning (ML) algorithm is applied to clarify wildfire vulnerability in Liguria. A group of algorithms from ML is used for the analysis, development, and visualization of the environmental data and work to model environmental risk [22].

Moreover, the characteristic of ML itself is a powerful and reasonable price and predicting wildfire. Because of that, ML is always has been chosen to monitor and see the trend and pattern of wildfire. Figure 1 shows the rise of a trend of using the computational intelligence method for analyzing GIS data nowadays proving that ML is welcoming [23]. In addition, these techniques have shown their skills in forming precise classification models that are used for wildfire mapping.

For instance, in Uttarakhand Himalaya, the pre-monsoon on wildfires is detected using satellite data, Landsat 8 OLI, and Sentinel 2 from 2016 until 2019. To complete the research, a combination of unsupervised and supervised robust machine learning (ML) is applied to identify the burn and unburned classification on Google Earth Engine (GEE) cloud platform [24]. The prediction of minimum height smoke in the atmosphere also used ML with utilized the variables that connected the fire activity, coordinate, and meteorology [25]. Besides, Cellular Automaton (CA) modeling is used to combine the conventional wildfire CA framework and Extreme Learning Machine (ELM). In this modeling method, the fire spreading model is created by ELM using the previous training data to validate the CA modeling is simply applied without a complex theory of conventional method and some physical parameters [26].

A figure showing the machine learning and data types, and modeling tasks with popular algorithms and potential applications in wildfire management. The bold algorithms are core ML methods while the algorithms non-bold are not considered ML. Many types of ML algorithms were used in wildfire applications, but this paper only reviews and focuses on the most frequently applied in wildfire science since 1990. Only Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Bayesian Networks (BN), Naive Bayes (NB), and Maximum Entropy (MaxEnt) algorithms were elaborate with details below.

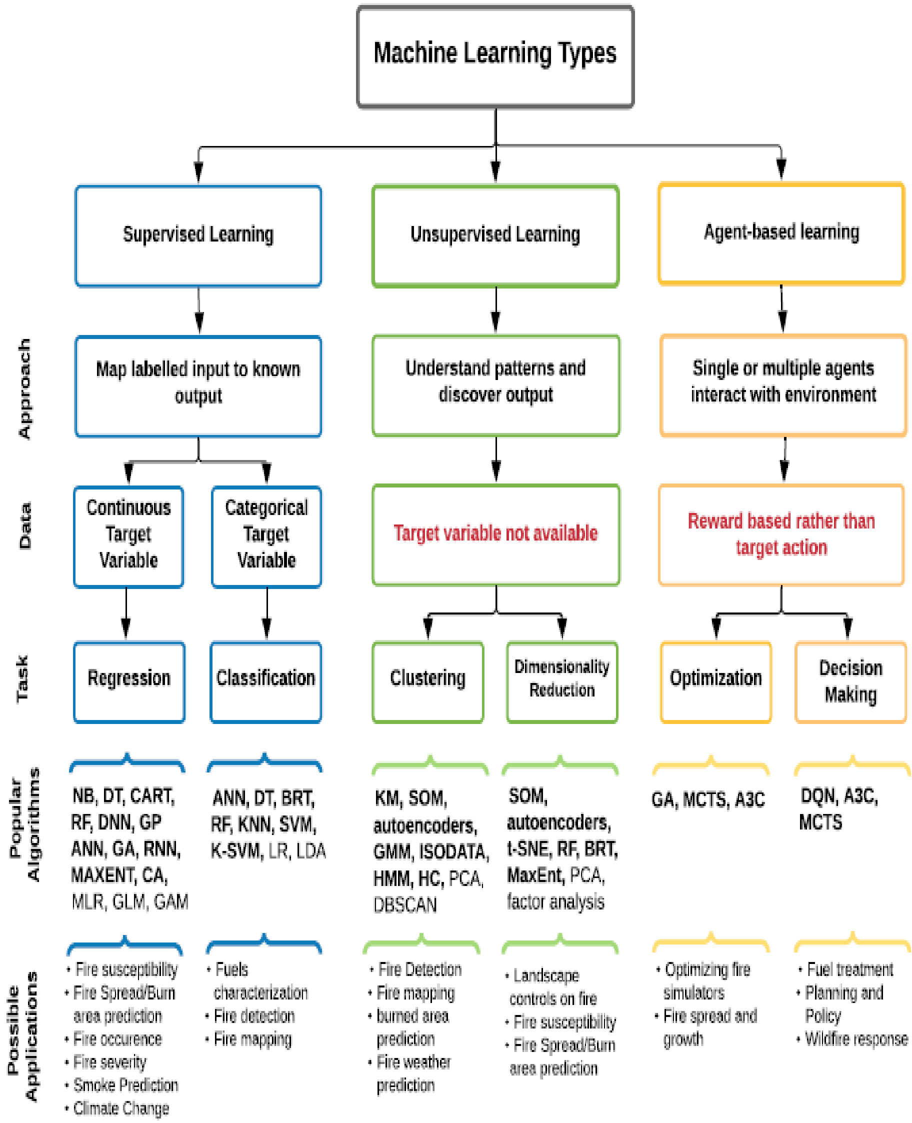

Fig. 1. Machine learning and data types and modelling task

3.3.1 Random forest

The Random Forest Machine Learning algorithm established by Breiman is a method that used bagging of tree regression and classification [27]. The significance of RF is to define the reason that affects the problem [31] with assign the class to the response variable. It is a very effective tools to solve the miscellany of pixel and object-based classification issues caused by robustness, accuracy, and processing speed (Figure 2) [28]. The majority votes or by averaging from the class classification will appointed as class prediction [27,29,31]. Mean Decrease Accuracy (MDA) and Mean Decrease Gini (MDG) are the two components that are applied to define the essential affective factors [31]. Random Forest is a merge of two third data set samples as a training set and another third work to validate the model [27].

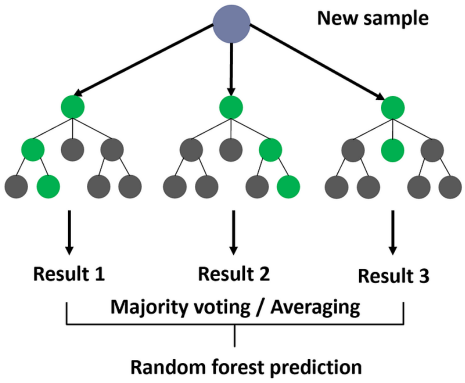

Fig. 2. Random forest structure

3.3.2 Support vector machine (SVM)

Figure 3 show Support Vector Machine (SVM), is a supervised Machine Learning algorithm that was suggested by Vapnik [30]. It is used as an optimal hyperplane idea for classification. In wildfire application, SVM is applied to separate the two classes (fire and non-fire) by doing the SVM map into high dimensional feature space to obtain the maximum margin of the two classes [32]. The area between the maximum margin will create the hyperplane classification [33]. The acquired value of the hyperplane can be used to forecast the class's possession.

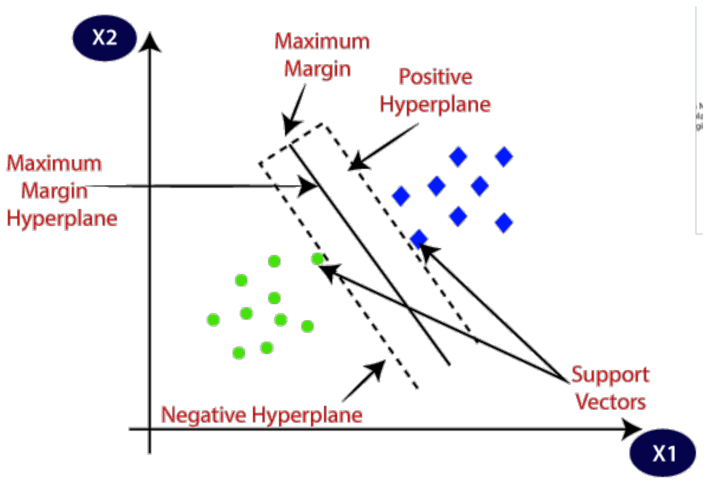

Fig. 3. Support vector machine (SVM) structure

3.3.3 Artificial neural network (ANN)

Artificial Neural Networks (ANN) is a subset of Machine Learning (ML) and it is known as a way of simulating the human brain to process artificial neurons (Figure 4) and make decisions [34], [35]. Artificial Neural Network (ANN) is an idea that can be explained as a detailed computerized design based on the idea of the human brain. Also, it is an information processing design device to determine and show the relationship between various data sets independently [36].

ANN is capable to solve problems and model of a nonlinear relationship between convoluted variables [34]. It involves numerous processing units recognized as neurons or notes that are utilized to obtain, process, and deliver data to each other across various convoluted connections [37]. Furthermore, ANN has been effectively harnessed to resolve various problems and it worked to reduce errors between the network input and network output vectors for the purpose to determine the best solution. ANN is a famous tool for classification and prediction, such as for regression and statistical models [38]. Moreover, prediction by using the ANN model as a machine learning tool frequently reaches a better final result compared to the other tools [39]. Therefore, the ANN model is a learning machine model that is suitable for prediction.

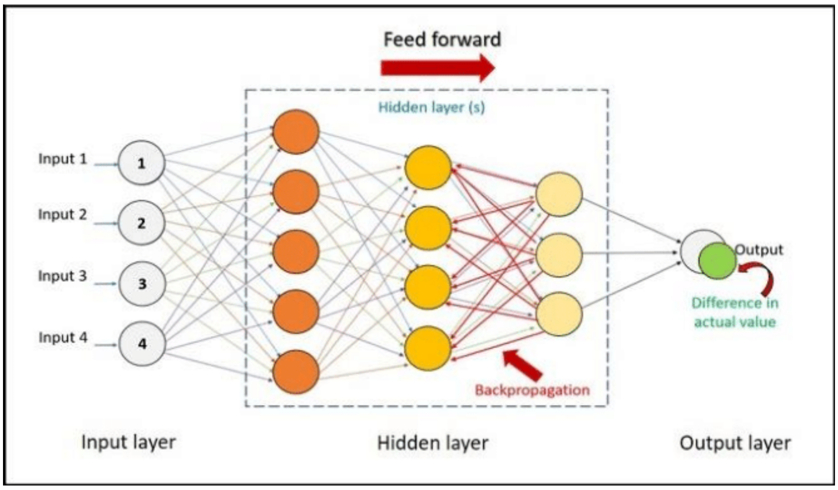

Fig. 4. Artificial Neural Network (ANN)

3.3.4 Bayesian methods

3.3.4.1 Bayesian networks (BN)

Bayesian networks also recognized as Bayes net or belief networks are accessible tools for calculating the resulting probabilities [40] which stipulate a graphical language to show the probabilistic relationships between variables, representing the data set. BNs contain nodes and arrows (or arcs) which is a directed acyclic graph to explicate the variables *U* in a probability distribution [21]. The set of parents of a node (variable) *X,* represented πx, are all nodes address the arcs getting into *X*. BNs portrayed a conditional distributions, where $p(X_i|X_{1,\dots}X_{i-1}) = p(X_i|\ \pi x_i)$, where $X_{1,\dots}X_{i-1}$ is set to be all of the forebears of X_i apart from its parents. Each node *X* is related to a probability table *X* and its parents are explained as $p(X_i|\ \pi x)$. If a node does not have parents, it is known as *p(X)*. The combination of a probability distribution of the network is then quantified as P(U) = $\Pi_{X\epsilon u}\ p(X|\pi_X)$.

BNs are causal networks or influenced diagrams, which are probabilistic network models which use the combination of the probability principle and the graph concept. Currently, the Convolutional Neural Network (CNN) has turned out to be a crucial deep learning algorithm, and it's can be relevant in many fields [41].

Bayesian networks (BNs) have earned their name for effective techniques for solving complex problems including unsure knowledge [40]. Furthermore, BNs are also perfectly competent to support decision-making conditions. To evaluate the fire incident, [42] a fire risk plan at Swaziland is modelled using Bayesian Network (BN), Geographic Information Systems (GIS) and remote sensing data. In another study, the fire risk reduction is evaluated using the BN model [43], [44] and it is also used to predict the wildfire distribution in Cypress island [28].

3.3.4.2 Naïve bayes (NB)

Figure 5 shows a Naïve Bayes (BN) is the simplest structure model among the Bayesian network models. The parent node is from the classification note from other nodes. There are no other links that are acceptable in a Naïve Bayes model. Naïve Bayes acted as an applicable classifier before this. The BN creation process is straightforward because the structure is offered a prior and very effective due to the variables being independent of each other [45]. Consequently, although NB is fast and easy to carry out, the output accuracy can be low where the supposition of conditional independence does not happen [21].

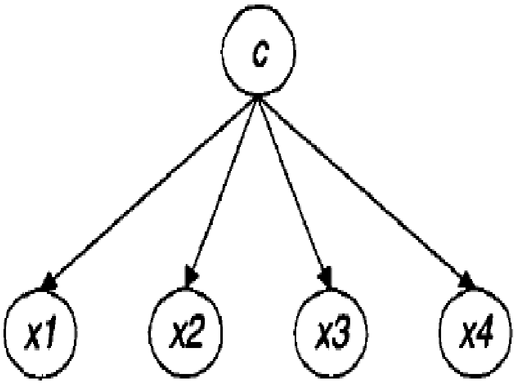

Fig. 5. A simple Naïve Bayes structure

3.3.4.3 Maximum entropy (MaxEnt)

Maximum Entropy (MaxEnt), formerly presented by Philips *et al.,* [46], is a framework that matches a spatial probability distribution by maximizing entropy, reliable with current knowledge [21]. MaxEnt can be deemed as a Bayesian method as it is well suited to the Bayes Theorem application which is known as specifying a prior distribution. MaxEnt is popular in landscape ecology species distribution modeling [47] where the research is involved the occurrence observations for the interest species.

4. Wildfire Application

As eloquently stated by World Wide Fund (WWF), wildfires usually happen at tree crowns. It starts with burning the leaf litter, dead branches, and finally vegetation on the ground surface. Wildfire action is depending on weather, fuel characteristics, and land topography. Other than that, wind direction also influences the direction of the fire spread. Many researchers reported that fire spread faster in warmer temperatures and dry weather. To lessen the possibility of burning as much as possible, monitored burns must be thought of, well prepared, and kept managed by trained experts.

The conventional method needs a lot of equipment and costs a lot. However, the gap is filled since the introduction of remote sensing and Machine Learning for environmental monitoring [48]. Based on the history of the earth observing satellites for environment management began nearly four decades ago [49]. GOES and Landsat satellites have been known to operate and aid the management of air pollution since the late 1970s [49]. In addition, various wildfire applications applied Machine Learning and satellite imagery. In this review paper, Fire Detection, Fire Mapping, Fire Occurrence Prediction, and Fire Susceptibility Mapping using ML will be discussed.

4.1 Fire Detection

A fast rate and efficient response need to be taken after the wildfire is detected to avoid it spreading wider and resulting in loss of life and properties. The usual method of wildfire detection by people is when they recognize smoke from their field of view, tower, or video. All these techniques can be restricted by human error, and the existence of smoke may be from other costs like factories and temporal coverage. Automated recognition of high-temperature signs or smoldering and infrared sensors or optical images can broaden the exposure of detection. Utilizing ML is suitable to better discern the issue and operated the wildfire classification, which is an analytic part.

From the previous study, ANN is applied in image processing for fire detection with support from meteorological data and other variables [50–53]. Besides this, the SVM algorithm also has been applied to accomplish this task [54,55]. The weakness of the SVM method is it inept to extract spatial features and results in a low accuracy, which is below 50% compared to ANN and Convolutional Neural Networks (98%) [56]. If BN was also applied for fire detection in the previous study, the result can improve fire detection and lessen the current error rate [57].

4.2 Fire Mapping

Fire risk mapping is advantageous to avoid big losses in the economy. It operates by evaluating and predicting the impact of wildfires on the economy and ecology. By organizing fire mapping, we can reduce the risk of fire burning. To achieve that, precise and comprehensive information on the spatial distribution is required to classify the risk area [21,58]. Researchers had been applying remote sensing for wildfire risk mapping since the 1970s with classify risk fire areas as active or inactive burned areas [59].

In the early 2000s, the researchers using ML to do the burned area mapping for fire detection had been expanding [60,61]. Mitrakis *et al.,* [62] used numerous ML algorithms such as ANN, SVM, Fuzzy Neuron Classifier (FNC), and AdaBoost to complete the burned area mapping in the Mediterranean. Besides that, there are a lot of studies using the SVM algorithm to perform the burned area mapping using remote sensing imagery [63–68]. Bayesian Updating of Land Cover (BULC) is applied by Crowley *et al.,* [69] by combining a few types of satellite images including MODIS, Landsat OLI, and Sentinel 2. While ANN and interactive Iterative Self-Organizing Data algorithm (ISODATA) is utilized by Sunar *et al.,* [70] to map the burned scar areas. In another research for the same objective, Quintano *et al.,* [29] used the MaxEnt model to complete the task.

Moreover, Bayesian networks (BN) and GIS technologies are among the techniques that have been used nowadays. From the previous studies, the Bayesian network model is created to forecast the potential wildfire causes and make an analysis of the simultaneous interactive interactions among them [71]. On other hand, it can estimate fire risk [42] and can do the processing procedures created using machine learning BN, GIS and remote sensing data [1] also recorded.

4.3 Fire Occurrence Prediction (FOP)

Fire Occurrence Prediction has been operating all around the world to detect, observe and evaluate fire activities [7,72]. This is beneficial to prepare for the worst. FOP models usually use a regression approach to give responses. ANN method is widely used to predict active fire. About 85% Vega-Garcia *et al.,* [73] predictions are accurate for non-fire and 78% for fire observation using ANN. Furthermore, in Galicia Spain, Alonso-Betanzos et *al.,* [74] predict daily active fire based on temperature, humidity, rainfall, and fire history variables by applying the ANN method, while the SVM algorithm is operated by Sakr *et al.,* [75] with using the same meteorological variables [75].

In addition, Sakr *et al.,* [76] applied SVM and ANN methods to compare fire occurrence prediction using relative humidity and precipitation. Random Forest become one of the options recently to predict active fire because of higher accuracy and prediction [33,77,78]. MaxEnt is also suitable to predict fire occurrence [79]. Overall, the Random Forest and Neural Network were the best two methods of Machine Learning with 94% and 91.8% accuracy [7]. The combination of ML model and GIS technology is used to analyze and predict the wildfire using past data. The variables that affect wildfires are different based on the study area. The precision of the result is more precise with long-term data and more variables included.

In other studies, Sivrikaya *et al.,* [80] studied that located in the Mediterranean region of Turkey and used the same parameters as their conditioning factors which are topographical, meteorological, vegetation, and anthropogenic factors. But Sivrikaya and Kucuk used official historical fire records [80] and Iban and Sekertekin used active fire pixels derived from MODIS monthly MCD14ML [81]. Besides that, Sivrikaya and Kucuk used the AHP model and statistical index (SI) as their weight for every factor with a score of 0.775. While Iban and Sekertekin applied machine learning (ML) with accuracy scores ranging from 0.812 and 0.879 from Random Forest (RF). Hence, the ML method that does not bother with subjective bias gives better results compared to MCDM yet MCDM used official historical fire records.

4.4 Fire Susceptibility Mapping

Wildfires are important environmental concerns. The loss of flora and fauna species means to give a problem to the carbon cycle or greenhouse gas emission. Wildfires also devote to unforeseen changes in land use thus increasing the risks of floods, soil and nutrient loss, and deficit in groundwater availability [82]. To overcome this risk problem, it is important to identify and justify this wildfire for protecting the loss of habitat of plant and animal species. For preparation and lessening the risk of fire, a further study has been carried out to understand the problem. The dynamics of vegetation, climate conditions, and physical environment are evaluated separately to minimize the frequency of fire incidences or destruction affected by fire [83].

Moreover, a few researchers also applied opinion-based methods like fuzzy logic, AHP, and ANP the analytical network method to illustrate the wildfire susceptibility map. AHP and ANP are multicriteria decision-making (MCDM) methods and facilitates operational research dealing with complex problem comprising different variables, differing objectives, and subjective criteria. This method ranks the criteria and changes them based on the decision maker's decision [84]. A decision maker can identify the value based on the significance or weights of criteria or variables. Nevertheless, the knowledge-based method may be idiosyncratic. Furthermore, the method still is afflicted by some theoretical disagreements and decision-makers need to answer a lot of questions [85].

Antithesis with a knowledge-based method, ML does not bother with subjective bias. These methods also involved the ambiguity related to the modeling of phenomena. Nevertheless, ML can be afflicted by model overfitting issues. ML models strongly depend on the training data set. To get an accurate result with a clarified relationship among the variables, the ML model necessitates a lot of data acquisition for an appropriate training model.

Table 1 is an example of a study that applied the ML technique. For example from the previous studies, a fire hazard map in Northeast Iran by Adab used Artificial Neural Network (ANN) and Binary Logistic Regression (BLR) method and found the Area Under Curve (AUC) event obtained 87%, while BLR obtained 81% [86]. Goldarag *et al.,* [87] used ANN and linear regression for the same application in Northern Iran with an accuracy of 93.49% for ANN, and 65.76% for linear regression. While other studies used the MaxEnt method as their option to model the ecology species classification [88]. Of further note, Bayesian Network (BN) model is used by Bashari *et al.,* [89] and Dlamini [90]–[92], Neuro-Fuzzy by Jaafari *et al.,* [93], the Random Forest model by R Luo *et al.,* [94], as well as SVM [63][30]. Fires susceptibility mapping in Yunnan Province China by G. Zhang *et al.,* [95] showed Conventional Neural Network (CNN) lead compared to other ML methods (RF, SVM, ANN, and Kernel Logistic Regression (KLR)) with 87.9% accuracy.

On other hand, the Bayesian Network model and GIS technology method [90], [92] were used in more than 90% of accuracy assessments were accurate and have a high degree of predictive accuracy. To improve the result of real-time fire risk, long-standing fire data and meteorological data must be included [90]. In the Swaziland research area, land cover is the most significant factor followed by the topography, rainfall and temperature were the major influence of wildfire activities [92]. In other studies, wildfires highly occurred in forests and sugar plantations. Grassland and bushlands are categorized as moderate and low [90]. In Mugla, Turkey, the probability of wildfire starts and occurs when the low wind speed, low rate of humidity, high temperature, lightning, and high human population in that area [85].

A. L. Achu *et al.,* [96] used about 10 types of ML to test the capability of the ML technique in southern Western Ghats, India. The study involved twelve influencing factors including air temperature, wind speed, rainfall, relative humidity, atmospheric water, vapor pressure (VWP), elevation, slope angle, topographically wetness index (TWI), slope aspect, land use land cover (LULC), distance from the road and distance from the villages. The AUC of each type of metal is mentioned in Table 1. Besides that, M.C. Iban and A. Sekertekin applied Logistic Regression (LR), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and ensemble algorithms namely Random Forest (RF), Gradient Boosting (GB), eXtreme Gradient Boosting (XGB) and AdaBoost (AB) in their study [81]. Topographical, meteorological, vegetation, and anthropogenic data were collected to test the ML method. Each study used different variables based on the topology and climate of the study area.

In the end, they used the SHAP (Shapley Additive explanation) to decipher the output values classified by the ML models. SHAP describes the output of the ML models in terms of the values of wildfire conditioning factors. In other words, Shapley values explain the influence of all the parameters or variables at the final prediction, and they can define whether the involvement of each parameter is positive or negative. In this study, the SHAP evaluation shows that the chance of wildfires boosts with higher elevation and higher slope values linked with lower temperature in these models.

Table 1
Example of review articles that applied ML in wildfire susceptibility mapping

Author	Title	Study Area	Model / Variable	Result
Dlamini [90]	Application of Bayesian networks for fire risk mapping using GIS and remote sensing data	Swaziland	Bayesian network (BN) Altitude, slope angle, slope aspect, mean annual rainfall, mean annual temperature, relative humidity, land tenure, soil class, road density, human population density, distance to settlements, livestock density and land cover	Accuracy assessments of the active fire and burned area data were 93.14 and 96.64%
Du et al., [97]	Random Forest and Rotation Forest for fully polarized SAR image classification using polarimetric and spatial features	Urban area	Random Forest and Rotation Forest, SVM (evaluation) Polarimetric Synthetic Aperture Radar (PolSAR)	Rotation Forest more accurate than SVM and Random Forest, in the but Random Forest faster than Rotation Forest
Satir et al., [83]	Mapping regional forest fire probability using artificial neural network model in a Mediterranean forest ecosystem	Upper Seyhan Basin (USB) in Turkey	Artificial neural network Relative Humidity, Temperature, Wind speed, Road maps Settlement locations, Farmlands, DEM, Tree cover, Fire locations, Fire magnitudes	Correlation coefficients: elevation (R = -0.43), tree cover (R = 0.93) and temperature (R = 0.42)
Zheng et al., [65]	Forest fire spread simulating model using cellular automaton with extreme learning machine	west of United States	Extreme Learning Machine (ELM) cellular automaton	ELM done well in predicting igniting forest fire probability] and the validation of simulation performance better than previously research.
Tonini et al., [61]	A machine learning-based approach for wildfire susceptibility mapping. The case study of the Liguria region in Italy	Liguria region in Italy	random forest DEM, Slope, Northness and Eastness, Distance to anthropogenic features, Protected area, Vegetation type, Non-flammable area, Neighboring vegetation	RMSE, lower values in summer (69.17 - 75.15) than in winter (79.28 - 87.03)
Bui et al., [98]	Spatial pattern analysis and prediction of forest fire using new machine learning approach of Multivariate Adaptive Regression Splines and Differential Flower Pollination optimization: A case study at Lao Cai province (Viet Nam)	Lao Cai province (Viet Nam)	Multivariate Adaptive Regression Splines (MARS) optimized by Differential Flower Pollination (DFP) Hotspot, slope, aspect, elevation, land use, distance to road, normalized difference vegetation index, rainfall, temperature, wind speed, and humidity	(AUC=0.91 and CAR=86.57%) better than Artificial Neural Network, fuzzy

Bar et al., [63]	Landsat-8 and Sentinel-2 based Forest fire burn area mapping using machine learning algorithms on GEE cloud platform over Uttarakhand, Western Himalaya	Uttarakhand, Western Himalaya	Classification Regression Tree (CART), Random Forest (RF), and Support Vector Machine (SVM) Landsat-8 and Sentinel-2	CART and RF overall accuracy of 97–100% but slightly lower in SVM. The Burnt area of Sentinel-2 lower accuracy than Landsat-8.
Yao et al., [64]	Predicting the minimum height of forest fire smoke within the atmosphere using machine learning and data from the CALIPSO satellite	West coast of Canada.	Random Forest Planetary boundary layer height above land surface (PBLH), Elevation, Latitude, Longitude, Direction, Daytime, Month	R^2 = 0.82 and root mean squared error is 560 m. assessment of ground-level population exposure to forest fire smoke should be improved
Pourghasemi et al., [99]	Assessing and mapping multi-hazard risk susceptibility using a machine learning technique	Fars Province (SE Iran)	Random Forest (RF) floods, forest fires, and landslides	AUC of flood (0.834), Landslide (0.939), and forest fire susceptibility maps (0.943)
Gigović et al., [30]	Testing a new ensemble model based on SVM and random forest in forest fire susceptibility assessment and its mapping in Serbia’s Tara National Park	Serbia’s Tara National Park	Support vector machine, random forest, ensemble model Distance from roads, distance from rivers, distance from urban areas, NDVI, temperature, wind power, rainfall, historical forest fire, topography, soil type, land use, road network	The AUC value for ensemble model is 0.848, SVM model is 0.844, and RF model is 0.834.
Arpaci et al., [100]	Using multi variate data mining techniques for estimating fire susceptibility of Tyrolean forests	Tyrol, Eastern Alps	MaxEnt and Random Forests Socio-economic, Infrastructure, Forest type, vegetation, Topography, Climate	The highest degree of importance are climate and population density variable.
Su et al., [77]	Using GIS and random forests to identify fire drivers in a forest city, Yichun, China	Yichun, China	Ripley’s K(d) function and Random Forests topography, vegetation type, infrastructure, meteorology, and socio-economic factors	Highest influence is fire history, meteorological factors and infrastructure. RF accuracy is 82.9%
Montorio et al., [78]	Unitemporal approach to fire severity mapping using multispectral synthetic databases and Random Forests	Zaragoza, Spain	Random Forest (RF) Landsat-8 and Sentinel-2A	The significance of spectral bands differs depends on ground cover type, and different bands boost fire susceptibility assessment.
Kaky et al., [101]	A comparison between Ensemble and MaxEnt species distribution modelling approaches for conservation: A case study with Egyptian medicinal plants	Egypt	Maximum Entropy (MaxEnt) Temperature, Precipitation, Altitude	AUC=0.90, TSS=0.83

Rahmati et al., [102]	Application of GIS-based data driven random forest and maximum entropy models for groundwater potential mapping: A case study at Mehran Region, Iran	Mehran Region, Iran	Random Forest and Maximum Entropy Altitude, Lithology, Drainage density, Landuse, Distance from rivers, Soil texture, Slope percent, Slope aspect, Plan curvature, TWI	MaxEnt (AUC = 87.7%), RF model (AUC = 83.1%)
Mpakairi et al., [103]	Distribution of wildland fires and possible hotspots for the Zimbabwean component of Kavango Zambezi Transfrontier Conservation Area	north-western Zimbabwe	Maximum Entropy Temperature, Population, Elevation, NDVI	AUC = 0.78
Amici et al., [104]	A multi-temporal approach in MaxEnt modelling: A new frontier for land use/land cover change detection	Italian Southern Alps	Maximum Entropy land cover class for the two temporal (1976 and 2001)	AUC = 0.93 to 0.99
Kozoderov et al., [34]	Bayesian classifier applications of airborne hyperspectral imagery processing for forested areas	Tver region of Russia	Bayesian hyperspectral images	The accuracy for the young forests and for the mature forests are high but not for intermediate ages of the pine forests due to less learning sample

5. Conclusion

The review had shown that the implementation of ML techniques in wildfire and management has been steadily increasing since their first usage in the 1990s. Furthermore, many fields are using ML methods. The rise of accessibility of meteorological and satellite data makes it more interesting and valuable to apply the ML method together which effectively obtains spatial and temporal data. There are varieties of ML method are used nowadays. There was also a study that employed hybrid or ensembled ML to improve the accuracy of their study rather than using a stand-alone method. But each method came out with different results because of the factors that were used. On other hand, Bayesian Network (BN) method is rarely chosen as a strategy even though BN fits and is linked with enhanced classifiers. Compared with other Machine Learning methods, BN has a steep study curve because its computational is very complex. To evaluate the probability of one part of the network, all parts must be computed. Furthermore, the dearth of tools may impede the adoption of Bayesian Networks by wildfire researchers. Despite the disadvantages, BN is suitable for small and incomplete data. There is no minimum sample size required to perform the model and it is suitable for wildfire data variables that usually have missing data. On other hand, based on the review, the manual approach or the construction of methodology in Bayesian Network for environmental applications is typically not persuaded. To defeat this, the usage of remote sensing data and GIS techniques may help the Bayesian Network model in the future. The rise in the accessibility of wildfire data, and the increase of researchers that are using machine learning as a trend method nowadays should take the adaptation of Bayesian Networks and wildfire management. On other hand, there is a major change for the wildfire management community or researchers to explore and fully utilize using ML methods. Plus, the implementation of ML in environmental sciences is tough. Support, discipline, and integrity from the team can help to contribute more effective results. Hence, to put it all together, the wildfire management communities and researchers must be enthusiastic about offering applicable, high-quality, and freely accessible wildfire data to help Machine Learning practitioners.

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