Article

Predict the duration of forestfires using machine learning methods

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Abstract: Forest and urban fires are a major problem in the modern era that tests the endurance of governments to extinguish them. Fires can cause economic and ecological problems especially in the summer months. In modern times, the rapid development of Artificial Intelligence can be a weapon for predicting the evolution of fires or even for their prevention. Specifically, through Machine Learning, which is one part of Artificial Intelligence several methods have been incorporated to detect the duration of fires using data which are freely available from the Fire Service of Greece for a period of 10 years. For this purpose, a wide range of machine learning techniques were used on this data and the experimental results were more than encouraging.

Keywords: Forest fires; Machine learning; Neural networks; Decision trees

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1. Introduction

Forests play an important role in the ecological balance [1] of our planet as well as in our everyday life [2]. However, these ecosystems are threatened by various risks, the most important of which are fires [3–5]. Forest fires destroy the forest ecosystem [6–8] and can have devastating effects on local economies [9,10], with a significant impact also on tourism development [11–13] as well as in human health [14–16].

Since the risks of fires are great, governments must take measures and review them in the direction of fire prevention by analyzing data collected from fires that have broken out in recent history [17–19]. Also, local authorities have used techniques for forest fire monitoring, such as small UAVs [20], usage of a monitoring system based on GPRS and ZigBee wireless network [21], the iForestFire system [22] etc. Merino et al. suggested an Unmanned Aircraft System (UAS) [23] for forest fire monitoring. Also, Aslan et al. proposed a system [24] of wireless sensor networks for forest fire detection and monitoring. Recently, Serna et al. suggested a distributed system for fire monitoring using wireless sensor networks [25].

During recent years, machine learning techniques have started to play an important role in the prevention and treatment of forest fires. For example, Dwiasnati and Devianto proposed the usage of various machine learning methods for the classification of forest fire areas [26]. Also, Pang et al. suggested the usage of a series of machine learning models to forest fire occurrence prediction in China [27]. Dampage et al. suggested a system of wireless sensor networks with data handled by machine learning models for the detection of forest fires [28]. Shao et al. proposed a mapping of China's forest fire risks using a series of machine learning models [31]. A parallel SVM model is also suggested by Singh et al. [29] for forest fire prediction on data collected from India and Portugal. A survey on machine learning models used for forest fire prediction can be found in the work of Abid [30].

In addition, image processing has been established as a fire detection method. In this direction, a multitude of techniques have been presented that also take advantage of machine learning methods, such as the work of Vicente and Guillemant that presented a method for early smoke source detection [32]. Also, Yan et al. proposed a method [33] that combined image processing techniques and neural networks for forest fire recognition. Mubarak et al. suggested a rule - based image processing algorithm [34] for forest fire detection. Convolution neural networks were utilized in the work of Wang et al. [35] for forest fire image recognition. Also, wavelet analysis was used in the work of Jiao et al. [36] for forest fire detection.

This research work focuses on the use of machine learning techniques to predict the duration of forest fires, which occurred in Greece from 2014 until 2023. The data was collected by the Hellenic Fire Service and then, after clearing missing records, the data was digitized and one of three categories was assigned to every pattern: fires of short duration, fires of medium duration and fires of long duration. The prediction of the duration of a fire is important as in this way, on the one hand, an estimate can be made of the expected damage that will be caused in the area, and on the other, the human resources required to extinguish the fire can be calculated. Similar works in this area include the work of Liang et al. that used the duration of a wildfire and the burnt area to determine the scale of wildfires using neural networks [37]. Also, KC et al.. proposed a Surrogate model [38] to model the size of a wildfire over time, using data collected from wildfires in Tasmania. Furthermore, Xi et al. proposed [39] the application of joint mixture models to model the duration and the size of wildfires.

The rest of this article is divided as follows: in section 2 the used dataset is described as well as the incorporated machine learning methods, in section 3 the experimental results are fully described and finally in section 4 some conclusions are discussed accompanied by some guidelines for future research.

2. Materials and Methods

This section presents the datasets that will be used in the experiments as well as the machine learning techniques that will be applied to these datasets.

2.1. The used datasets

In this research work, open data was used which is available from the Hellenic Fire Service at the relevant link https://www.fireservice.gr/en_US/synola-dedomenon(accessed on 14 September 2024). The data was obtained for the years 2014-2023 and data preprocessing techniques were applied before inputting the data into machine learning models.

The initial datasets contain information in both numerical and alphanumeric form, such as the area in which the forest fire occurred or the fire station that extinguished it. Therefore, the first step in preprocessing the data was to digitize the columns that contained numerical information and replace them with a discrete integer. The next important step in the preprocessing of the original data is to delete the records that contain empty values in various attributes. This could happen, for example, if a value was not available at the time of entry. Those records in which the duration of the fire was zero were also deleted. Then, to create the exit category, the duration of the forest fire was converted into minutes. Subsequently, three distinct values were created depending on the logarithmic value of the duration in minutes of the forest fire. This value will be used as the target value in running the experiments.

Having performed the previously mentioned preprocessing steps, the final datasets contain 25 features and the following information about the forest fires:

1. Fire department.
2. Province.
3. Season.
4. Burnt area: forest area, grove, grasslands, reeds/swamps, agricultural lands, cover crop, garbage dumps.
5. Personnel: Firefighters, volunteers, army, etc.
6. Vehicles: firefighting, tanks, etc.

7. Aerial means: helicopters, different aircrafts.

2.2. *The proposed algorithms*

A number of machine learning techniques were used to efficiently find classes in the datasets of the previous subsection. These techniques cover a wide range of techniques available in the field of machine learning and are presented in more detail below.

2.2.1. Bayesian Networks

Bayesian networks are probabilistic models based on direct acyclic graphs [40,41] and they have been applied with success in various cases. For example, Friedman et al. used Bayesian Networks to analyze expression data [42]. Also, Cai et al. used Bayesian Networks in fault diagnosis [43] and Barton et al. proposed the use of Bayesian Networks to environmental problems [44]. In the case of forest fires, Bayesian Networks have been used in many cases, such as to predict and analyze possible fire causes [45]. The study was conducted in Mugla of Turkey. Also, Bayesian networks were used to model the cascading impacts of drought and forest fire in a recent study [46]. Also, Bayesian Networks were combined with deep learning for detection of fires from video frames [47].

2.2.2. Naïve Bayes

The Naïve Bayes is a supervised machine learning algorithm, used for classification tasks. This classifier, uses principles of probability in order to perform classification tasks [48,49]. This algorithm has been incorporated in many research areas, such as document classification [50], traffic risk management [51], network intrusion detection [52] etc. Also, the Naive Bayes has been used in forest fire issues in a series of papers. For example, Nugroho et al. proposed a system for forest fire prevention using a combination of a wireless sensor network and a Naïve Bayes classifier [53]. A classification of hotspots causing forest fires using the Naive Bayes algorithm is proposed in the work of Zainul et al. [54]. Karo et al. proposed a methodology to classify wildfires using feature selection and the Naive Bayes among other machine learning methods [55]. Also, a variant of the Naïve Bayes Algorith was suggested by Shu et al. for forest fire prediction [56].

2.2.3. Logistic Regression

Like the previously mentioned algorithms, Logistic Regression, works also with machine learning classification and it can be considered as a data analysis technique used to predict probabilities [57]. Cabrera proposed the Logistic Regression for higher school decisions [58]. Also, Lawson et al. proposed the usage of Logistic Regression method to analyze customer satisfaction data [59]. Hu and Lo used the Logistic Regression technique to model urban growth in their paper [60]. This method has been used also in a series of issues involving forest fires, such as human - caused wildfire risk estimation [61], prediction of wildfire vulnerability [62], probabilistic modeling of wildfire occurrence [63], analysis of wildfire danger [64]etc.

2.2.4. Artificial neural networks

Artificial neural networks (ANNs) are parametric models [65,66], where a set of parameters, commonly called weights, must be calculated to be adapted to classification or regression data. This machine learning model has been utilized in a variety of scientific and real - world problems, such as physics problems [67–69], solving differential equations [70,71], solar radiation prediction [72], agriculture problems [73,74], problems appeared in chemistry [75–77], wind speed forecasting [78], economics problems [79–81], problems related to medicine [82,83] etc.

In the area of forest fire prediction and observation, a number of works using artificial neural networks have been published. Hossain et al. used ANNs to detect flames and smoke from static image features [84]. Lall and Mathibela utilized neural networks to predict the risk of wildfires in the city of Cape Town [85]. Also, Sayad et al. used neural networks among other machine learning techniques for predictive modeling of wildfires from data collected from NASA's Land Processes Distributed Active Archive Center (LP DAAC) [86]. Artificial neural networks and meteorological data were used in the work of Liang et al. to predict the scale of wildfires [87]. Also, a case study for predicting wildfires for a Chinese province using neural networks was published recently by Gao et al. [88].

2.2.5. The J48 algorithm

The J48 algorithm [89] is one of the most used supervised machine learning algorithms, used to construct decision trees for classification data. This method was tested on a series of classification problems, such as prediction of diabetes [90], network intrusion detection [91], classification of criminal data [92], fingerprint gender classification [93], fake news classification [94] etc. Also, the J48 algorithm was used to predict forest fires using data from Slovenia in a recent work [96]. A similar study was performed in Algeria using the J48 algorithm among other machine learning models [96].

2.2.6. Random Forests

Random Forest [97,98] is a popular supervised machine learning algorithm, used to construct decision trees for classification problems. The method of Random Forests has proven its adaptability and effectiveness in a number of difficult problems, such as remote sensing classification [99], ecology issues [100], bionformatics [101], text categorization [102], network intrusion detection [103] etc. Moreover, random forest was incorporated for forest fire prediction, such as in the work of Latifah et al., where random forests were applied to predict forest fires in Borneo [104]. Also, Malik et al. proposed the usage of Random Forests for wildfire risk prediction in Northern California [105]. Also, Gao et al. performed a forest fire risk prediction [106] in China using a combination of Random Forests and a neural network trained with the Back Propagation method [107].

3. Results

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Table 1. Experimental results using various machine learning models for 10 years of observations.

YEAR	BAYESNET	NAIVEBAYES	LOGISTIC	MLP	J48	RANDOMFOREST
2014	11.44%	12.89%	9.81%	11.37%	10.04%	9.42%
2015	11.08%	11.26%	9.53%	10.65%	9.51%	8.95%
2016	25.71%	13.00%	3.41%	3.90%	3.65%	3.00%
2017	11.04%	11.51%	9.48%	10.08%	10.30%	9.29%
2018	11.20%	10.46%	9.09%	9.48%	9.27%	8.58%
2019	9.61%	9.25%	8.29%	8.53%	9.08%	8.01%
2020	18.00%	6.72%	5.54%	5.97%	6.09%	5.50%
2021	12.35%	14.15%	12.04%	13.59%	13.59%	11.92%
2022	10.25%	9.62%	9.01%	9.47%	9.04%	8.93%
2023	9.74%	9.19%	8.26%	8.77%	8.39%	7.66%
AVERAGE	**13.04%**	**10.81%**	**8.45%**	**9.18%**	**8.90%**	**8.13%**

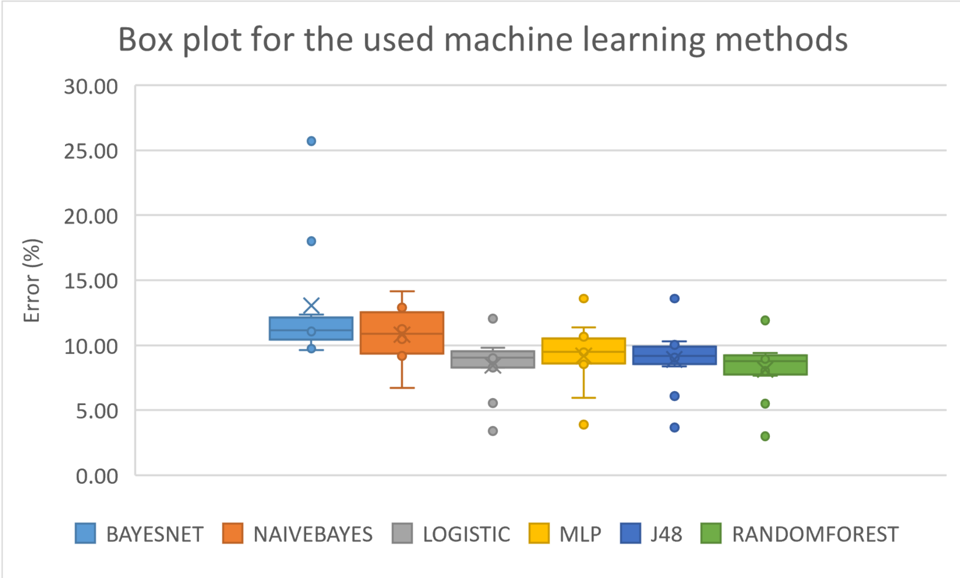

Figure 1. Box plot for the used machine learning techniques.

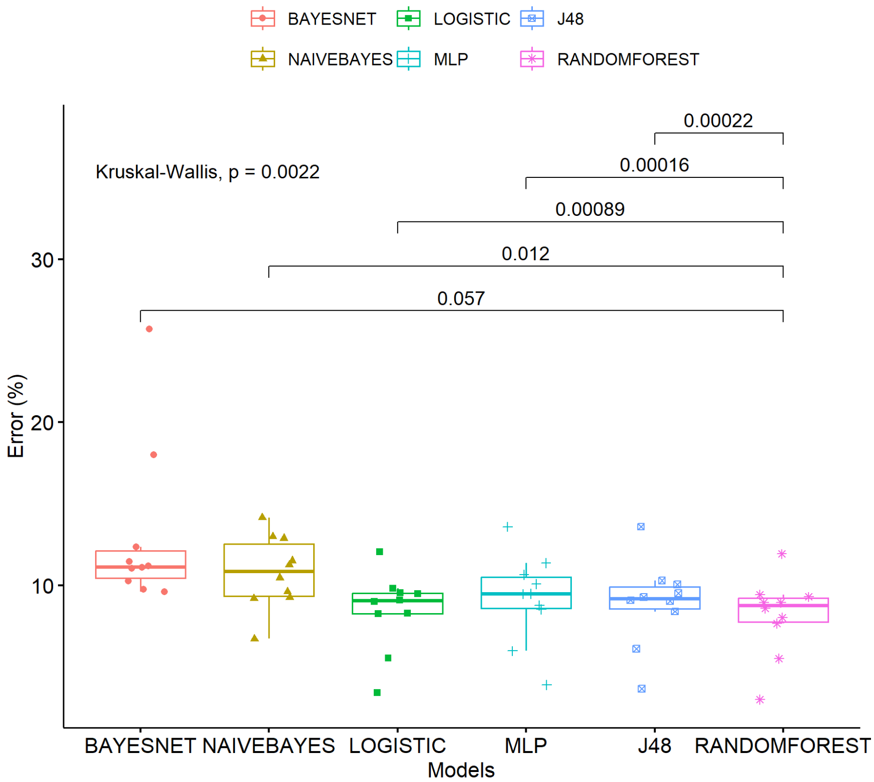

Figure 2. Statistical comparison between the Random Forest method and the other machine learning methods.

4. Conclusions

1) Discover important features for predicting duration
2) create rules for determination of categories
3) using meteorological data

Author Contributions: C.K., V.C. and I.G.T. conceived of the idea and the methodology, and C.K. and V.C. implemented the corresponding software. C.K. conducted the experiments, employing objective functions as test cases, and provided the comparative experiments. A.S. performed the necessary statistical tests. All authors have read and agreed to the published version of the manuscript.

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