Use of hybrid artificial intelligence models combined with machine learning, big data, and IoT technologies for forest fire prediction and management

Efthimiou Vasilios[1], Eleftheriadis Anastasios[2], Iosifidis Efstathios[3], Mavromatis Panagiotis Fotios[4], Tzelalis Georgios[5]

[1] Efthimiou Vasilios, ics21035@uom.edu.gr
[2] Eleftheriadis Anastasios, ics22135@uom.edu.gr
[3] Iosifidis Efstathios, iis21027@uom.edu.gr
[4] Mavromatis Panagiotis Fotios, ics21073@uom.edu.gr
[5] Tzelalis Georgios, ics21032@uom.edu.gr

Konstantinos E Psannis
kpsannis@uom.edu.gr

Abstract

Fires are considered one of the most dangerous and destructive phenomena in the world, affecting the environment, the local population, and the economy. Modern research has been carried out using artificial intelligence, machine learning, big data, and IoT to create a model to predict and respond to fires. Today, a success rate of up to 99.09% in predicting a fire has been achieved thanks to a hybrid artificial intelligence algorithm Adaptive Neuro-Fuzzy Inference System - Imperialist Competitive Algorithm. Meanwhile, the implementation of Digital Mobile Radio nodes and the use of SIoT, Lysis, were also studied. The system has been tested and trained in a real outdoor scenario, proving its effectiveness, with up to 98% correct fire detection rate. The combination of the two approaches makes a major contribution to the prediction and response to forest fires.

Keywords: *artificial intelligence, machine learning, big data, prediction, fire, algorithms, IoT, DMR, DMR, Lysis, ANFIS, ICA*

1. Introduction

1.1. Fire probability prediction

Fires, whether man-made or caused by natural causes such as drought, wind, lightning, and vegetation, are considered one of the most dangerous and destructive phenomena in the world. The intensity and frequency of fires have increased worldwide to an alarming level. It is estimated that they destroy thousands of square kilometers of forest every year, affecting the environment, local people, the economy, and health. Their complexity lies in the fact that they are difficult to predict, as they combine complex meteorological phenomena, complex topography, and complex fuel sources (Sayad et al., 2019). In addition, tracking and predicting the course of a fire that has already broken out requires the collection of various weather parameters in real-time (e.g., air temperature, wind speed, soil moisture), which is difficult, especially when data collection from inaccessible and hazardous areas is required (Sayad et al., 2019).

Prediction of fire probabilities is based on the existence of variation in the spatial probability of forest fire occurrence given the characteristics of the area. The prerequisite for successful estimation of this variance is that fire occurrences are associated with a set of explanatory variables that can be measured. These variables include landscape characteristics, climate, and anthropogenic factors that influence when and where fires break out (Jaafari et al., 2017a).

1.2. Forest fire modeling approaches

Various approaches have been proposed for modeling forest fires, such as the natural-based method, the statistical method, and others, however, here we will focus on the machine learning method. The works studied can be divided into two broad categories: those that use machine learning (ML) and image processing and those that use sensors to analyze environmental parameters.

1.3. Machine learning methods

Among these methods, Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machines (SVM), Random Forests (RF), and Classification and Regression Tree (CART) have often been used in the context of fire modeling and in many cases have outperformed conventional statistical methods (Oliveira et al., 2012; Rodrigues and de la Riva, 2014; Guo et al., 2016; Bui et al., 2017).

In particular, neural networks (NN) have been used to predict human-caused fires (YO Sayad et al., 2019), and have been combined with infrared scanners to reduce false fire alarms with 90% accuracy (Arrue, 2000). In addition, Spatial Clustering (Spatial Clustering FAS-TCiD) has been adopted to locate fire spots in satellite imagery (Hsu et al., 2002), and in 2005 satellite images of North American fires were fed into a Support Vector Machine (SVM) for fire detection at the 1.1-km pixel level with 75% accuracy.

Artificial intelligence (AI) methods have the advantage that they can be combined with many other methods to improve model quality (Bui et al., 2017; Termeh et al., 2018), while for fire prediction, they have the potential to provide detailed knowledge of spatial patterns of fire occurrence (Bui et al, 2017; Termeh et al., 2018), which can be used as key input parameters for forest fire management and suppression in the context of urban planning, rural development, and ecosystem conservation.

1.4. Hybrid modeling

Since 2013, hybrid modeling of natural disasters has received increased attention due to the greatly enhanced predictive accuracy of natural phenomena (Tehrany et al., 2013). As a data collection method, remote sensing is often used to ensure real-time data acquisition from inaccessible and hazardous locations (Sayad et al., 2019). Big Data is undergoing rapid growth estimated at 4TB per day and is reduced to a high rate of data generation, efficient data processing, and analysis (YO Sayad et al., 2019).

1.5 AI and IoT use

Fire risk prevention and mitigation practices are marginal and inadequate. Therefore, early detection plays a very important role. Recently, hybrid monitoring techniques have evolved through the use of cameras and AI tools that partially replace the human factor. Technically, the development of high-performance digital cameras, increasingly advanced image processing techniques, and the use of ML algorithms have made it possible to create firefighting systems based entirely on image processing. The use of ML techniques makes it possible to identify a situation of potential danger. In addition, we have various embodiments for air quality monitoring. The environmental information is forwarded from the nodes to the IoT social platform called Lysis via Digital Mobile Radio (DMR), where it will be analyzed and correlated through a Recurrent Neural Network (RNN) in order to detect fire hotspots in time (Pettorru et al., 2023).

1.6. Methodology for approaching the topic

In this paper, we analyzed the findings of the most recent research related to the topic of forest fire prediction and response using Big Data, machine learning, IoT, and artificial intelligence. We have tried to understand the complexity of the issue by considering all the factors that make it difficult to deal with it and gathering all the competent and necessary data required so that we can then use them collectively to address the problem. We observed the intersection of research on whether Big Data, machine learning, IoT, and artificial intelligence have the potential to predict forest fires and if so, under which conditions and circumstances the best result is achieved. We have drawn our own conclusions which we have recorded.

1.7. Structure and organization of the paper

In Section 2 we summarize the research that outlines the efforts that have been made to model forest fires using modern technology. In Section 3 we present the result of the research that emerged as the most efficient. Finally, in Section 4, we report the conclusions drawn from the combination of the results of the literature review.

2. Literature review

2.1. From regression models to hybrid modeling of natural disasters

Since 1990, starting with the pioneering work of Chuvieco and Congalton (1989), regression models have been widely used in modeling fire probabilities. However, recent comparative studies have shown that traditional regression models (e.g., linear and logistic regression) fail to accurately estimate spatial patterns of fire probabilities because they assume a linear relationship between fire occurrence and the factors that cause it. It is widely accepted that the causes of forest fires act nonlinearly within a wide range of spatiotemporal scales and therefore require nonlinear models to handle complex processes.

To date, several hybrid forest fire modeling methods have been studied, starting with Bui et al. (2017), who showed that a hybrid ANFIS method with PSO was more successful for forest fire prediction than advanced methods, and continuing with Abolfazi Jaafaria, Eric K. Zennerb, Mahdi Panahic, and Himan Shanabid who tested even more models.

2.2. A hybrid approach to artificial intelligence

In the research of Dieu Tien Bui, Quang-Thanh Bui, Quoc-Phi Nguyen, Biswajeet Pradhan, Haleh Nampak, Phan Trong Trinh in 2017, a hybrid artificial intelligence approach called Particle Swarm Optimized Neural Fuzzy (PSO-NF) was tested for spatial prediction of tropical forest fire susceptibility. In the proposed approach, the Neural Fuzzy Inference System (NF) was used to establish the forest fire model, while the PSO algorithm was adopted to explore the best values for the model parameters. The PSO-NF model was tested in Lam Dong province located in North Vietnam, which has been severely affected by forest fires in the last fifteen years.

To model the fires, historical fires and ten ignition factors (slope, aspect, elevation, land use, land use, normalized difference vegetation index -NDVI-, distance to road, distance to habitable area, temperature, wind speed, and rainfall) were collected to construct a geographic information system (GIS database) with a total of 540 historical fire locations in 2013, the year with the most drought in the last three decades. The data were collected from the official national database on forest fires in Vietnam, national topographic maps, and the Climate Forecast System Reanalysis (https://www.ncdc.noaa.gov/). The database was then used to develop and validate the proposed model. 70% of forest fires (378 fires) were used for model training and the remaining 30% for validation (162 fires), and since forest fire modeling can be considered binary classification, the same number of non-fire points were used.

To evaluate the adaptability and fire prediction ability of the sensitivity model, statistical metrics such as overall success rate, positive predictive value, negative predictive value, specificity, and sensitivity were used. In addition, the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) were used.

The results showed that among all ignition factors considered, the "Normalized Difference Vegetation Index (NDVI)" has the highest fire predictive ability (0.659). It was further shown that the proposed model performs well on both the training dataset (AUC = 0.932) and the validation dataset (AUC = 0.916).

Since this research was the first to propose the PSO-NF model for tropical forest fire modeling, the usability of the model was further evaluated through comparisons with two advanced machine learning methods, Random Forests (RF) and Support Vector Machines (SVM). RFs were chosen because they have outperformed conventional methods for fire modeling, while SVMs were chosen because they are widely accepted as effective methods for nonlinear and complex problems. The comparison showed that the two advanced machine learning methods have high prediction ability, however, their overall prediction rate is slightly lower than that of PSO-NF (PSO-NF 85.8%, RF 85.2%, and SVM 84.9%). From the analysis, it is concluded that the PSO-NF model is the most suitable for the studied area.

2.3. Combining neuro-interface with metaheuristic optimization algorithms

In a comparative analysis by Abolfazl Jaafari, Eric K. Zenner, Mahdi Panahi, and Himan Shahabi conducted in 2019, an ANFIS model was combined with a metaheuristic optimization algorithm. ANFIS integrates artificial neural networks and fuzzy logic principles in a single framework to deal with nonlinear functions predicting chaotic time series and has been widely used for natural disaster prediction (Jang, 1993; Pradhan, 2013; Jaafari et al., 2017b, 2019; Chen et al., 2019).

The objective of this analysis was to determine whether a hybrid modeling approach exhibits superior accuracy for spatial prediction of fire probabilities compared to the stand-alone ANFIS model and to evaluate which metaheuristic optimization algorithm can most improve ANFIS for forest fire modeling. The algorithms tested were genetic algorithm (GA), particle swarm optimization (PSO), shuffled frog leaping algorithm (SFLA), and imperialist competitive algorithm (ICA).

A spatial database of 159 fire events from Iran and more specifically from Minudasht region during the period 2002-2014 was used to train the hybrid models. In recent years, the region consists mostly of pine forests (60%) and cultivated land (26%), which are prone to natural disasters such as fires. Fires in Minudasht mainly break out between June and October, with peak periods in July and August. Survey data were collected from the MODIS sensor on NASA satellites (https://www.earthdata.nasa.gov/learn/find-data/near-real-time/firms), from previous surveys, and from several field surveys. Unfortunately, details on the exact causes of the fires were not always thoroughly documented for each fire record. While field investigations indicated that many fires were indeed carried out by natural factors, some anecdotal reports suggest that small fires may have been caused by arson, especially those that broke out on farmland.

70% of the collected data (111 fires) were used for training the hybrid models, while the remaining 30% (48 fires) were used for validation. Still, as fire probability modeling is a binary classification task, where probability indices are classified into "fire" and "non-fire" classes, a set of 159 random non-fire locations from areas not prone to fires was also used for sampling.

A set of predictor variables was collected from the events and each variable was divided into classes. For spatial correlation analysis, the Step-wise Weight Assessment Ratio Analysis (SWARA) method was used to assign weights to each variable. The weights indicate how strong the spatial relationship between each class and fire occurrence is and were used to train the hybrid models.

Although the single ANFIS model outperformed the hybrid models in the training phase with a success rate of 99.34%, its accuracy decreased significantly in the validation phase (90.17%). The performance of ANFIS-ICA in predicting fires and mapping the dataset was remarkable with a prediction rate of 99.09%, and during training, it achieved a success rate of 99.31%, the second highest after ANFIS.

The hybrid intelligence models proposed in this research successfully improved the fire prediction accuracy by 18% compared to previous work that simply used single models in the study. This study is therefore a step forward in the field of natural hazard prediction by suggesting that hybrid, and perhaps more complex models, are consistently more accurate than simple single models.

2.4. ANN & SVM

In addition to hybrid AI algorithms, many AI techniques, such as Big Data, Remote Sensing, and Data Mining algorithms (ANN and SVM) for forest fire prediction are also proven.

The research of Younes Oulad Sayad, Hajar Mousannif, and Hassan Al Moatassime, combines exactly the above models to process data collected from satellite images of large areas and extract information from them to predict the occurrence of wildfires. For this purpose, a database was built with remote sensing data related to crop conditions (Normalized Difference Vegetation Index - NDVI - an index of photosynthetic activity of a crop, considered the most widely used vegetation index), meteorological conditions (Land Surface Temperature - LST, represents the radiant soil temperature, used to detect crops that need water) and the fire indicator "Thermal Anomalies" (gives immediate information about a fire that has already started) collected by the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA satellites - the database is available on GitHub: https://github. com/ouladsayadyounes/Wildfires -. These three parameters were chosen because the primary goal is to predict forest fires that are naturally caused by heat or lightning.

The study area consists of zones located in central Canada and primarily in British Columbia and Quebec due to their history of high fire rates and the availability of fire information, information

obtained from the Canadian Wildfire Information System (CWFIS). A total of 386 fire zones were selected between 2013 and 2014 for which remote sensing data (NDVI, LST, and Thermal Anomalies) were extracted and divided into "fire" and "non-fire" classes.
The results of the experiment demonstrate that the selected parameters (NDVI, LST, and Thermal Anomalies) can be used to predict the occurrence of a fire, however, they are not sufficient to evaluate the performance of the model. Therefore, multiple performance classification metrics were used to validate the model.
The models showed high fire prediction accuracy (ANNs: 98.32%, SVM: 97.48%). More specifically, the NN model was able to predict an average of 117 fire cases out of 119 total cases in the "fire" class, while the SVM model was able to predict 116 out of 119. Overall, the ANN model was able to successfully predict 214 fire cases out of 238 from both the "fire" and "no-fire" classes, while the SVM model was able to successfully predict 200 cases out of 238.
The results were better than the CFFDRS (Canadian Forest Fire Danger Rating System) prediction rate of 95.32%. A significant difference, as 3% can represent thousands of hectares and cost millions of dollars to save thousands of lives. CFFDRS is effective in limited areas of the world, whereas the model in this study can be used in any area of the world as long as satellite imagery is available. Also, CFFDRS predicts the occurrence of fires over wide areas, while the survey model predicts their occurrence in precise restricted zones.

2.5. Sensor system in a DMR node combined with SIoT social networking platform

The proposed system consists of 5 DMR nodes that operate independently from each other. Each node is equipped with sensors to detect forest fire smoke, as well as to measure temperature, humidity, atmospheric pressure, and UV index. The 4FM YSF NXDN DSTAR P25 DMR is the heart of the fire detection node. The node manages the main smoke detection sensor and sends a VHF/UHF signal to the DMR gateway. In addition, the node is powered by rechargeable batteries connected to a charge controller and a suitably sized solar panel. This node is based on a Raspberry Pi Zero 2W+ and a DMR standard-compliant transmission module (Pettorru et al., 2023). The BME688 4-in-1 sensor used for air quality (gas, temperature, atomic pressure, humidity) has updated characteristics as an air scanner that can react to volatile organic compounds (VOCs), volatile sulfur compounds (VSCs), and the presence of carbon monoxide and hydrogen to give a general air quality measure for indoor and outdoor environments. (Pettorru et al., 2023). A solar panel (10W 6V 1700mA 260x140x2.5mm) with USB support for working outdoors was appropriately sized so that it could support the energy needs of the node throughout the day, charging 3500mAh - 10A 18650 batteries (Pettorru et al., 2023).
The nodes are mainly in deep sleep mode to limit energy consumption. They are activated every 5 minutes to acquire sensor data, process packets, and wirelessly transmit the acquired data. The DMR gateway collects information from all DMR nodes (Appendix Figure 1a) and transmits the data to a social IoT (SIoT) platform called Lysis (Appendix Figure 1b) using the 4G LTE network. Lysis is a SIoT platform realized for distributed IoT applications involving socially connected objects. The detection timing plays a very important role in determining the direction of the origin of the firefront. Usually, the first nodes to detect smoke are the closest to the fire, so they are critical for determining the direction of the fire and applying appropriate countermeasures (Pettorru et al., 2023).
An artificial intelligence algorithm was developed within Lysis to identify fire cases through training conducted in the field through fire and smoke propagation simulations. Lysis collects sensor data and processes it through continuous comparison with previously stored data. The outliers are processed to avoid false positives and generate warning states (Pettorru et al., 2023).
The scenario used for the preliminary tests was applied in Sardinia (Italy) in the mountainous region of Pixina Manna (Pettorru et al., 2023).

3. Results

The results of Jaafari et al, (2019) are presented in detail below, as the most effective hybrid algorithms among the others reported in the literature review.

3.1 Correlation between historical fires and predictor variables

The relative change in SWARA weights in each category of each predictor variable indicates the different levels of spatial correlation between the predictor variables and fire occurrence. The results revealed that the most fire-prone parts of the landscape receive > 700 mm rainfall (Weight = 0.58), are located in scattered forests (SF) (Weight = 0.56), have a wind effect > 1.14 (Weight = 0.48), and proximity to settlements of 2.2-3.2 km (Weight = 0.47), respectively.

3.2 Model performance

The training and validation phases of the modeling process determined the relationship between the inputs (predictor variables and historical fires) and the output (probability of future fire). The value of objective functions (i.e., RMSE) ranged from 0.003 (ANFIS) to 0.224 (ANFIS-GA) in the training dataset and from 0.119 (ANFIS-ICA) to 0.296 (ANFIS) in the validation dataset revealed an asymmetry in the performance of the single ANFIS model. While in the training dataset this model showed the best performance, the results for the validation dataset revealed a significant decrease in performance, indicating an overfitting problem of the training dataset in the learning stage of the fire model. The results of the performance evaluation using other metrics further confirmed the overfitting of the single ANFIS model (Appendix Table 1). In contrast, the hybrid models performed quite well on both the training and validation datasets, demonstrating a successful refinement of the ANFIS parameters using the optimization algorithms.

As global performance metrics, the success rate and prediction rate (Appendix Table 1) also showed the overfitting problem of the individual ANFIS model. While this model achieved the highest training performance (success rate = 99.34%), the validation performance (prediction rate = 90.17%) of the model decreased significantly compared to the hybrid models. The different hybrid models differed little in their performance, with success rates between 99.2% and 99.3% and prediction rates between 98.1% and 99.1%, indicating high model performance for predicting future fires. In terms of convergence speed, ANFIS-PSO was found to yield an optimal convergent solution (RMSE = 0.156) with the fewest iterations (iterations = 191, time = 21 s), followed by ANFIS-ICA, ANFIS-GA, and ANFIS -SFLA, respectively (Appendix Figure 2).

3.3 Sensor system in a DMR node combined with SIoT social networking platform

DMR nodes detected an increase in temperatures and an increase in CO values during wood combustion. The system immediately returned responses detecting not only an increase in temperatures due to the presence of hot air caused by the fire but also notable temperature changes detected by the DMR nodes. In fact, the nodes closest to the source were the first to detect the temperature increase. Similarly, the other nodes farther away from the source "noticed" with a delay an external heat source that affected the normal diurnal temperature trend. The greater the distance between nodes, the smaller the temperature increase, Also, the greater the distance between the fire front and the DMR node, the longer the response time and the smaller the measure of the maximum temperature detected by the fire. An important observation to make is that the greater the distance between the fire source and the DMR node, the lower the CO concentration detected by the DMR nodes due to the greater dispersion of the detected smoke. Finally, Table I summarizes the confusion matrix of the collected data, which highlights the high accuracy (i.e., almost 98%) of the RNN in correctly detecting forest fires with very low false positive and false negative values. In addition, RNN correctly detects the absence of fire with a rate of almost 99%. The recursive structure of the RNN together with the work performed by the DMR-SVOs allows us to reduce the uncertainty cases by applying oversampling of the acquired data through queries performed by the SIoT Lysis platform on the DMR nodes. The RNN developed in the Lysys environment is concerned with detection:

1) fire development based on temperature and CO input values. When multiple nodes show a deviation of values beyond a certain threshold determined by the neural network training, the system notifies the fire initiation through alerts sent to police authorities, civil protection,

2) the propagation direction and speed of the fire front based on the detection order of DMR nodes. The system has been tested and trained in a real outdoor scenario, proving its effectiveness, with up to 98% correct fire detection rate.

4. Conclusions

Forest fires are one of the most dangerous natural hazards with devastating effects on society and the environment. They are complex processes that require advanced quantitative approaches to uncover their underlying patterns and elucidate the processes that drive these patterns. However, predicting natural hazards with a single method may lack scientific robustness because changes in the model and/or data can produce very different results. In other areas of science, researchers often address such problems using hybrid models, which are capable of producing more accurate results. The use of hybrid models can achieve superior performance in more efficient computing time.
From the literature we collected, the ANFIS - ICA hybrid model had the best results with a success rate of 99.09% in fire prediction and mapping of the dataset. The literature also studied the implementation of DMR nodes and the use of an SIoT, Lysis. The system has been tested and trained in a real outdoor scenario, proving its effectiveness, with a correct fire detection rate of up to 98%. The combination of the two approaches makes a major contribution to forest fire prediction and management and should be investigated by the civil protection of any country that systematically addresses the problem of forest fires.

5. References

Arrue, B.C., Ollero, A. and De Dios, J.M., 2000. An intelligent system for false alarm reduction in infrared forest-fire detection. *IEEE Intelligent Systems and their Applications*, *15*(3), pp.64-73.

Bui, D.T., Bui, Q.T., Nguyen, Q.P., Pradhan, B., Nampak, H. and Trinh, P.T., 2017. A hybrid artificial intelligence approach using GIS-based neural-fuzzy inference system and particle swarm optimization for forest fire susceptibility modeling at a tropical area. *Agricultural and forest meteorology*, *233*, pp.32-44.

Chen, W., Panahi, M. and Pourghasemi, H.R., 2017. Performance evaluation of GIS-based new ensemble data mining techniques of adaptive neuro-fuzzy inference system (ANFIS) with genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO) for landslide spatial modelling. *Catena*, *157*, pp.310-324.

Chen, W., Panahi, M., Tsangaratos, P., Shahabi, H., Ilia, I., Panahi, S., Li, S., Jaafari, A. and Ahmad, B.B., 2019. Applying population-based evolutionary algorithms and a neuro-fuzzy system for modeling landslide susceptibility. *Catena*, *172*, pp.212-231.

Guo, F., Zhang, L., Jin, S., Tigabu, M., Su, Z. and Wang, W., 2016. Modeling anthropogenic fire occurrence in the boreal forest of China using logistic regression and random forests. *Forests*, *7*(11), p.250.

Hong, H., Panahi, M., Shirzadi, A., Ma, T., Liu, J., Zhu, A.X., Chen, W., Kougias, I. and Kazakis, N., 2018. Flood susceptibility assessment in Hengfeng area coupling adaptive neuro-fuzzy inference system with genetic algorithm and differential evolution. *Science of the total Environment*, *621*, pp.1124-1141.

Hsu, W., Lee, M.L. and Zhang, J., 2002. Image mining: Trends and developments. *Journal of intelligent information systems*, *19*(1), pp.7-23.

Jaafari, A., Gholami, D.M. and Zenner, E.K., 2017. A Bayesian modeling of wildfire probability in the Zagros Mountains, Iran. *Ecological informatics*, *39*, pp.32-44.

Jaafari, A., Rezaeian, J. and Omrani, M.S.O., 2017. Spatial prediction of slope failures in support of forestry operations safety. *Croatian Journal of Forest Engineering: Journal for Theory and Application of Forestry Engineering*, *38*(1), pp.107-118.

Jaafari, A., Zenner, E.K., Panahi, M. and Shahabi, H., 2019. Hybrid artificial intelligence models based on a neuro-fuzzy system and metaheuristic optimization algorithms

for spatial prediction of wildfire probability. *Agricultural and forest meteorology*, *266*, pp.198-207.

Jaafari, A., Panahi, M., Pham, B.T., Shahabi, H., Bui, D.T., Rezaie, F. and Lee, S., 2019. Meta optimization of an adaptive neuro-fuzzy inference system with grey wolf optimizer and biogeography-based optimization algorithms for spatial prediction of landslide susceptibility. *Catena*, *175*, pp.430-445.

Jang, J.S., 1993. ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics*, *23*(3), pp.665-685.

Nami, M.H., Jaafari, A., Fallah, M. and Nabiuni, S., 2018. Spatial prediction of wildfire probability in the Hyrcanian ecoregion using evidential belief function model and GIS. *International journal of environmental science and technology*, *15*(2), pp.373-384.

Oliveira, S., Oehler, F., San-Miguel-Ayanz, J., Camia, A. and Pereira, J.M., 2012. Modeling spatial patterns of fire occurrence in Mediterranean Europe using Multiple Regression and Random Forest. *Forest Ecology and Management*, *275*, pp.117-129.

Pettorru, G., Fadda, M., Girau, R., Sole, M., Anedda, M. and Giusto, D., 2023, February. Using Artificial Intelligence and IoT Solution for Forest Fire Prevention. In *2023 International Conference on Computing, Networking and Communications (ICNC)* (pp. 414-418). IEEE.

Pradhan, B., 2013. A comparative study on the predictive ability of the decision tree, support vector machine and neuro-fuzzy models in landslide susceptibility mapping using GIS. *Computers & Geosciences*, *51*, pp.350-365.

Rodrigues, M. and De la Riva, J., 2014. An insight into machine-learning algorithms to model human-caused wildfire occurrence. *Environmental Modelling & Software*, *57*, pp.192-201.

Sayad, Y.O., Mousannif, H. and Al Moatassime, H., 2019. Predictive modeling of wildfires: A new dataset and machine learning approach. *Fire safety journal*, *104*, pp.130-146.

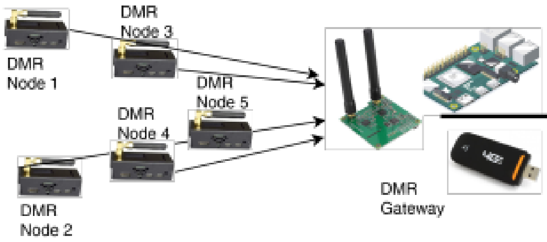
Tehrany, M.S., Pradhan, B. and Jebur, M.N., 2013. Spatial prediction of flood susceptible areas using rule based decision tree (DT) and a novel ensemble bivariate and multivariate statistical models in GIS. *Journal of hydrology*, *504*, pp.69-79.

Termeh, S.V.R., Kornejady, A., Pourghasemi, H.R. and Keesstra, S., 2018. Flood susceptibility mapping using novel ensembles of adaptive neuro fuzzy inference system and metaheuristic algorithms. *Science of the Total Environment*, *615*, pp.438-451.

Appendix

Metric	Training dataset					validation dataset				
	ANFIS	ANFIS-GA	ANFIS-PSO	ANFIS-SFLA	ANFIS-ICA	ANFIS	ANFIS-GA	ANFIS-PSO	ANFIS-SFLA	ANFIS-ICA
RMSE	0.003	0.224	0.156	0.145	0.146	0.296	0.166	0.165	0.150	0.119
Accuracy	1.00	0.97	0.98	0.98	0.98	0.95	0.98	0.98	0.98	0.99
Sensitivity	0.99	0.98	0.98	0.98	0.98	0.94	0.96	0.98	0.98	0.98
Specificity	0.99	0.96	0.97	0.97	0.97	0.92	0.95	0.97	0.97	0.97
False alarm ratio	0.01	0.08	0.03	0.03	0.03	0.04	0.02	0.02	0.02	0.02
Kappa	1.00	0.97	0.97	0.98	0.98	0.89	0.95	0.97	0.97	0.98
Success rate (%)	99.34	99.19	99.22	99.28	99.31	–	–	–	–	–
Prediction rate (%)	–	–	–	–	–	90.17	98.07	98.91	98.94	99.09

Table 1: Model performance on the training and validation datasets (Jaafari et al., 2019)



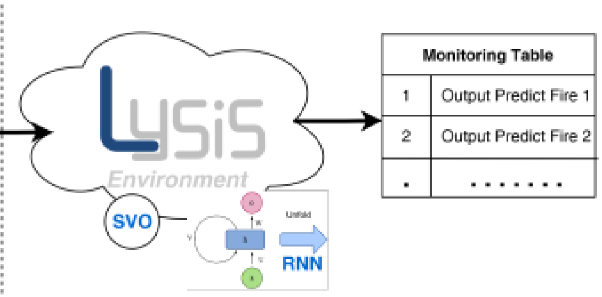


Figure 1a: Level 1 data acquisition, processing, and transmission (Pettorru et al., 2023).

Figure 1b: Level 2 data storage and visualization (Pettorru et al., 2023).

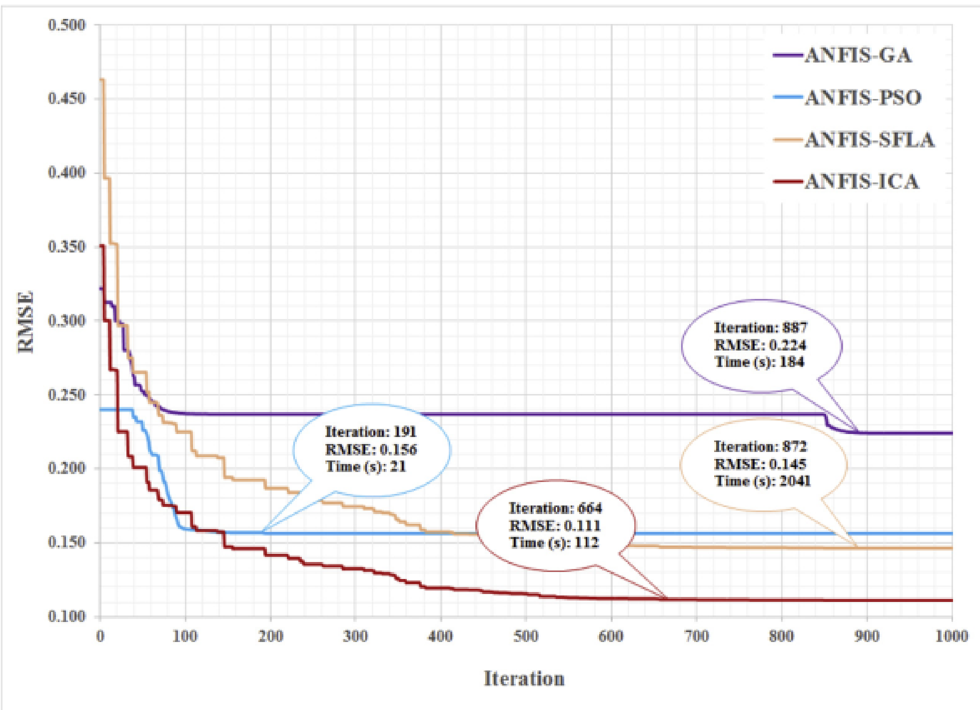


Figure 2: Convergence curve of the fitness function (RMSE) for the hybrid model. (Jaafari et al., 2019)